# The Paradox of Skill in Norwegian Mutual Funds

The thesis applies the bootstrap methodology of Kosowski (2006) on Norwegian Mutual funds to determine whether abnormal performance is due to luck or skill.

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**Abstract**

This thesis examines Norwegian mutual funds' performance, and specifically whether that performance is due to luck or skill under the null hypothesis of no true performance. We use an extensive dataset of 107 Norwegian mutual funds free of survivorship bias, over the period 1987-2019. We use the Carhart (1997) four-factor model as our performance model, both on the aggregate and individual level. On the aggregate level, we find no significant evidence for abnormal risk-adjusted returns. Looking at the funds on the individual level, we use a bootstrap approach to distinguish luck from skill. The bootstrap is implemented to evaluate our results' statistical significance, intricate dependencies in the cross-section, and the non-normal returns. We find no evidence of skilled managers in our top-performing funds. However, we find a clear indication of the lack of skill in our worst-performing funds.

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# 1 Introduction

This thesis is studying whether abnormal performance in Norwegian mutual funds is due to luck or skill. Hence the title, the Paradox of Skill in Norwegian Mutual Funds, luck plays an increasing determining role in the outcome as the level of skill required increases. We have two fundamental problems we would like to investigate: (1) Are Norwegian mutual fund managers able to produce significant positive alphas net of cost, and (2) are the performance based on luck or skill.

Fama (1970) introduced the efficient market hypotheses (EMH) claims one cannot outperform the market, and any successful attempt to do so is luck. More recent studies (Carhart, 1997; Edelen, 1999) show that the market is not operating fully efficient (Grossman and Stiglitz, 1980), and exploiting mispricing in the market over time is not truly manageable. Nevertheless, investors keep buying actively managed mutual funds again, raising the question of whether portfolio managers can outperform their benchmark. Actively managed portfolios buy and sell stocks according to a set strategy attempting to identify abnormal performance ex-ante and identify mispriced securities, pursuing to outperform a specific index. Portfolio managers engage the market by following shifts in market trends and the economy, political changes, and other factors potentially affecting a specific industry or company. The market cannot be fully efficient for exploitable mispricing to exist (Fama, 1970), as defined by EMH. Prices are determined by all available information fulfilling EMH; if the market were fully efficient, there would be no abnormal returns to exploit. One of the arguments is that any attempt to "beat" the market is a gambling game where results comprise of sheer luck. In order to examine whether there are any skilled or unskilled managers, we first have to evaluate if there are any active Norwegian mutual funds able to generate risk-adjusted returns net of cost.

The second problem is separating performance due to stock-picking skill from luck. We know from statistics that there will always be outliers that generate an abnormal performance in a large sample, both positive and negative. The challenging part is differentiating the lucky managers from the skilled ones. This thesis aims to investigate the performance of the actively managed Norwegian mutual funds and answer this fundamental question: Is there significant evidence of skilled or unskilled Norwegian mutual fund managers? We have identified 107 actively managed Norwegian mutual funds between January 1987 and December 2019 as a basis for our analysis to address this issue. A frequently applied approach in these studies has been testing for persistence in funds returns. Both Grinblatt and Titman (1992) and Carhart (1997) studied whether past top performers could persist in generating high returns and vice versa for the bottom performers. An essential issue in this approach is that the funds are ranked on short-term performance. We are instead using bootstrap simulations of previous returns ranked on their t-statistic of alpha. The bootstrap method of Kosowski, Timmermann, Wermers, and White (2006) is based on performance alpha derived from the Carhart (1997) four-factor model, allowing us to distinguish luck from skill in individual funds. We applied the bootstrap method to the monthly returns net of each fund's cost and ensuring sufficient statistical assumptions. We ran 10,000 bootstrap simulations, and to conclude whether skilled managers exist, we compared the cross-section of alpha estimates for actual fund returns to the bootstrap simulations' alpha estimate distribution. Instead of basing our assumptions on the parametric t-test, we depend on the bootstrapped p-value.

Most literature and research are based on U.S. mutual funds resulting in only a handful of broad and extensive studies on the Norwegian mutual fund market relevant to our thesis hitherto. Gallefoss, Hansen, Haukaas, and Molnár (2015) is one of the few published papers on the Norwegian mutual fund market. The study evaluates Norwegian mutual funds in 2000-2010, applying the bootstrap method (Kosowski et al., 2006) on the funds' daily returns. They find that top funds outperform bottom funds in terms of both stock-picking and market-timing abilities, claiming that the difference is too large to be explained by luck alone. Sørensen (2009) does not provide evidence similar to Gallefoss et al. (2015). Referring to Malkiel (1999) popularized thesis stating that it still bears some truth in that a blindfolded monkey throwing darts at the Wall Street Journal's financial pages could do as well as financial experts. Sørensen (2009) says the data makes it hard to disagree with Malkiel's recommendation to buy broad-based index funds with low expenses, identifying no evidence of skilled managers, only unskilled managers. Our study takes on a different time horizon than previous studies covering a substantial part of the Norwegian mutual fund market's existence. Due to messy data in some areas in the early- to mid-1980s, we start in 1987, enabling each fund to be consistent. As there are few comprehensive studies on the matter in Norway, we believe that our thesis will be a valuable contribution to the existing literature.

Our results indicate that the aggregate, Norwegian mutual fund managers generate an abnormal return that is not significantly different from zero. Therefore, lacking the necessary skill to achieve performance exceeding the cost of their services. Our bootstrap results indicate that individual funds submit no significant evidence on superiority. Looking at the inferior performers, we contrarily found evidence of lack of skill generating negative risk-adjusted-performance. In many of our underperforming funds, we find a significant value; only in our worst performer, the value is not significant, which could be an anomaly. We found evidence at a 95% level of certainty on the individual level of unskilled managers among inferior performers, and no evidence of skill among top fund managers.

The thesis structure is given by chapters addressing relevant matters, building up to the empirical analysis and results. A literature review of relevant studies and academic papers is given in chapter 2, and chapter 3 comprises models and methods. Chapter 4 contains our dataset and various properties, criteria, and assumptions necessary to produce the empirical results in chapter 5. Chapter 6 includes remarks and conclusions.

# 2 Literature Review

This section reviews previous studies and academic literature on mutual fund performance, bootstrap, and luck and skill in mutual funds. The focus of this chapter is to brief our reader the most relevant studies and papers done on this subject, establishing expectations for our findings. The first part will review historical literature essential in understanding performance evaluation in finance before we examine the literature and the implementation of the bootstrap procedure in measuring luck versus skill.

## 2.1 Performance of Mutual Funds

Mutual fund performance is a well-researched topic in the last decades since 1968, and it all started with Markowitz (1952). He created the field of portfolio theory, where the idea of financial diversification started to grow. Following this, Sharpe (1964), Lintner (1965), and Mossin (1966) created the Capital Asset Pricing Model (CAPM). CAPM is a crucial piece in Economic theory and something every economics student has been introduced to from an early stage, also being one of the fundamentals of this paper. Sharpe (1964) created the first evaluation of risk-adjusted performance on mutual funds, the Sharpe Ratio. Sharpe (1966) utilized his ratio to evaluate 34 open-end U.S. mutual funds between 1945 and 1963. The conclusion from this study was that 11 funds performed above the benchmark and 23 performed below. Sharpe argued in his study that the U.S. market was highly efficient, concluding that investing in actively managed mutual funds was a poor investment.

Jensen (1968) created the single-factor model, which he based on the CAPM. Jensen used this as his evaluation tool of risk-adjusted performance on mutual funds, creating what we now know as Jensen's alpha. Jensen's alpha is an estimation of the abnormal performance of the mutual fund, stating that in theory, an actively managed mutual fund should create a positive alpha, opposed to a passive index generating an alpha of zero.

Jensen (1968) performed his valuation of 115 U.S. mutual funds in the period 1945-1964, using alpha as an evaluation tool. Jensen concluded that mutual fund managers, on average, are not able to generate positive alphas, after collecting their fees (net of cost). Ippolito (1989) argued against Jensen's findings in 1968. By using a sample of 143 U.S. mutual funds between the period 1965-1984, Ippolito (1989) found evidence that mutual funds outperformed the S&P500 index net of cost.

Following Jensen (1968), arguments were presented contesting the use of proper benchmark when evaluating mutual fund performance. Roll (1977) presented a paper where he disputed the use of CAPM proxy as the benchmark when evaluating mutual funds' performance. The main critique about CAPM as a proxy is because CAPM assumes all investors have the same complete knowledge and strategy. An abnormal return is only possible in an inefficient market; hence there is no complete information. This sparked a debate about the use of benchmarks. In the paper by Lehmann and Modest (1987), they presented evidence that the choice of benchmark impacts Jensen's alpha. They discovered that the results are sensitive to the benchmark and argued the need for an appropriate benchmark that accurately represents common factors determined by security returns. Following these findings, Elton, Gruber, and Blake (1996) argued that the positive alpha of Ippolito (1989), was generated out of an inappropriate benchmark. They investigated the funds in Ippolito's (1989) portfolio and found a high amount of small stocks that were not listed in the S&P500 benchmark, and these stocks had a significantly high return. After adjusting this, Elton found that Ippolito's (1989) positive alpha turned negative.

Furthermore, Malkiel (1995) performed a research on all the U.S. mutual funds returns over the period from 1971 until 1991. He concluded in his study that the mutual funds underperformed. However, his results as the ones before him are sensitive to the choice of benchmark. Since the choice of benchmark is highly sensitive, this led to the creation of a multifactor model, which controls for various anomalies in the market. The most used and famous models are Fama and French (1993) three-factor model and Carhart (1997) four-factor model. Fama and French (1993, 1996) extended Jensen (1968) single-factor model and add two factors, size (SMB) and value (HML). Carhart (1997) extends the three-factor model and adds a one-year momentum factor of Jegadeesh and Titman (1993).

One of the early adopters of the four-factor model for evaluating mutual funds was Gruber (1996), where he studied mutual funds between 1985 and 1994. Gruber (1996) used a four-factor multifactor, which was the excess market return, the difference in return between small- and large-cap portfolios, the difference in return between high growth and a growth portfolio, and excess return of a bond index. Gruber's (1996) model advocates a slight underperformance of mutual funds, compared to an appropriate weighted average of indices. However, Gruber (1996) argued that fund managers could achieve an abnormal return, gross of expenses. He concluded that managers could pick stocks, but their fees were not justified. Thus, investing in these funds was not worth it for an average investor.

Daniel, Grinblatt, Titman, and Wermers (1997) performed an extensive evaluation of 2,500 U.S. equity mutual funds between 1975 and 1994, with the primary purpose to unveil whether managers have sufficient stock-picking skills to justify their fees. They researched whether the funds' excess return was connected to Characteristic Selectivity and Characteristic Timing. Daniel et al. (1997) discovered that mutual fund managers exhibit a certain level of stock-picking abilities, more specifically in aggressive-growth funds with an annual positive alpha. However, the alpha was very close to the managerial fees, which makes it a neutral performance for the funds. This is where the paradox of skill comes into play as they could not find any evidence of having an ability of Characteristic Timing. Fama (1970) introduced the Efficient Market Hypothesis (EMH) claims one cannot outperform the market, and any successful attempt is basically luck. The market needs not to be inefficient for fund managers to exploit mispricing (Fama, 1970) as defined by EMH.

Edelen (1999) examined 166 U.S. mutual funds, using the Jensen (1968) single-factor model, applying the CRSP value-weighted index that reported a significant negative average alpha of -1.63% per year with an expense ratio of 1.72%. This indicates that managers do very little besides collecting fees. Edelen (1999) concludes that the negative alpha is a result of fees and not lack of managerial stock-picking abilities. Blake and Timmermann (1998) conducted extensive research on 2,300 U.K. mutual funds between 1972 and 1995. Following this research, they reveal that the average U.K. mutual fund underperforms by about 1.8% on a risk-adjusted basis. Otten and Bams (2002) collected and examined data for 506 mutual funds in Germany, France, Italy, Netherlands, and the U.K. The study controlled for survivorship bias and did not eliminate funds that were terminated over the researched period. They applied the four-factor model of Carhart (1997) on the net returns of the European countries and found that every country except Germany produced a positive alpha, net of costs. German mutual funds had an underperformance with a negative alpha, but not a significant one. After accounting for the fees, the U.K. funds were the only funds with a significantly positive alpha.

Wermers (2000) examined the performance of U.S. mutual funds in the period between 1975 and 1994 and broke down the mutual funds' performance based on net return and stock holdings. Wermers (2000) discovered a difference of 2.3% in returns for the average mutual funds and the return on stock holdings. In particular, holding stocks outperformed the market; however, he concluded with a negative net return. Specifically, the difference was mainly due to expenses and transaction costs, the remainder could be accounted for as an underperformance of non-stock holdings. Moskowitz (2000) critiqued these results from Wermers (2000), specifically on the use of Wermers benchmark. Moskowitz (2000) debated that the benchmark consisted of small and risky firms. Specifically, these firms performed generally poorly over the sample period, skewing the results. Following this, the results that Wermers (2000) found could be inflated.

According to the research we have discussed so far in this thesis, we are struggling to find evidence that proves managers exhibit stock-picking abilities. Most of the papers found evidence of negative alphas; however, this does not explicitly mean that every individual fund is not able to overperform and generate a positive alpha. Grossman and Stiglitz (1980) argue that some mutual funds overperform, and some underperform, due to momentary mispriced securities in the market.

## 2.2 Scandinavian Studies

Previous research made on Scandinavian mutual funds is far from as comprehensive as U.S. studies. We take a closer look at the most relevant ones: Dahlquist, Engström, and Söderlind (2000), Korkeamaki and Smythe (2004), Sørensen (2009), Christensen (2013) and Gallefoss et al. (2015).

Dahlquist et al. (2000) studied the performance and characteristics of Swedish mutual funds from 1993 until 1997. They found evidence for neutral performance in most of the types of equity funds, but they found an overperformance in regular equity funds. They concluded in their study that there was evidence that supported that actively managed funds performed better than passive (index) funds. Korkeamaki and Smythe (2004) researched Finnish mutual funds between 1993 and 2000, which generally exhibit neutral performance. Specifically, the equity funds primarily provided negative performance. Sørensen (2009) performed an extensive evaluation of Norwegian mutual funds using the bootstrap procedure of Kosowski et al. (2006), with the modifications of Fama and French (2010), to evaluate the funds on an individual level for the period between 1982 and 2008. The mutual fund sample size if free of survivorship bias, and on an aggregate level, he was not able to find any significant proof of managers being able to generate a positive alpha. Sørensen (2009) concluded in his study that there is no clear evidence of an overperformance in the right tail of the cross-sectional distribution of alpha. However, in the worst-performing funds, there is evidence of a lack of skill leading to an abnormal negative performance.

Christensen (2013) examined 71 Danish mutual funds in the period between 2000 and 2010. He concluded that 57 of these funds generated negative alphas, where 23 proved to be significant. Only a total of 5 funds yielded significant positive alphas. Interestingly, Christensen (2013) discussed that investors pay a front-end fee when entering a mutual fund and a back-end fee when they leave the fund. This would reduce the alpha even further, leading to an even more significant part of the funds generating a negative alpha or a neutral alpha. Gallefoss et al. (2015) examine Norwegian mutual funds between 2000 and 2010 using daily data. They applied the bootstrap method of Kosowski et al. (2006) and discovered significant evidence of an abnormal over- and underperformance on an individual level. Specifically, they found evidence of managers possessing stock-picking abilities, and lack of it, in over- and underperforming funds. On the aggregate level, however, they concluded that the funds underperform their benchmark.

From these studies in both sections, we want to determine whether the performance of Norwegian Mutual funds in the period 1987-2019 is due to luck, or if it is based on stock-picking skill. To further enlighten this subject, we have considered more recent studies on luck versus skill.

## 2.3 Luck versus Skill

To enable us to distinguish luck from skill among Norwegian mutual fund managers, we have applied the method of Kosowski et al. (2006). This paper applied a cutting-edge bootstrap method to help address whether individual mutual fund performance can be credit managerial stock-picking skill or is due to luck. The bootstrap method has a few essential advantages as it removes the requirement of specifying the exact shape of the distribution from which returns are drawn (Kosowski et al., 2006). Another important notion is explicitly controlling for data snooping. White (2000) presented data snooping, also known as data mining, as a pitfall when doing statistical analysis from an ex-post sort using simulations such as the bootstrap method. Data snooping occurs when looking for correlations in a massive data sample, but only a small subset is reported. Despite no exploitable forecasting relation is present in the sample, studying it at lengths may provide forecasting models looking usable, but is in fact meaningless. White (2000) applied what is known as Bootstrap Reality Check, or White's Reality Check, which Kosowski et al. (2006) in their method also applied in this paper. (Kosowski et al., 2006) discovers that the top and bottom 10% of the mutual funds could not be explained by luck. Hence, Kosowski et al. (2006) concluded that the top performers were due to skill, and the bottom 10% was due to a lack of skill.

As data snooping occurs when "the more scrutiny a collection of data is subjected to, the more likely will interesting (spurious) patterns emerge" (Lo and MacKinlay (1990, p.432), it is argued that the risk of data snooping (mining) biases will increase the more the topic is studied. Regarding our topic, studying luck versus skill in the cross-section of the alpha distribution, the chance of abnormal findings or patterns is relatively high. Yan and Zheng (2017) focused on fundamental-based variables, where the variables were derived from financial statements. They claim that the findings in previous studies mostly have been considered without accounting for the waste amount of search preceding them, yet documented hundreds of cross-sectional return anomalies. They evaluated the data-mining bias in cross-sectional return anomalies by using a bootstrap approach and examining fundamental signals derived from financial statements. Yan and Zheng (2017) found that even after accounting for data mining, there are elements that significantly predict cross-sectional stock returns. The predictive ability found is more pronounced in small, high-volatility stocks and evidence of expectation and mispricing errors being the reason for fundamental-based anomalies, and not a product of data mining (Yan & Zheng, 2017).

The False Discovery Rate (FDR) was suggested by Barras, Scaillet, and Wermers (2010) to separate fund performance based on luck from skill-based performance. They applied the bootstrap method of Kosowski et al. (2006) and further developed new FDR measures (FDR among the best and the worst funds) which allowed them to individually target the right and left tails of the cross-sectional alpha distribution and measured the impact of luck on the funds' performance. Based on 1,456 US open-end equity funds between 1975 and 2002 and found that while the standard approach derived that 7.1% are skilled, after they accounted for luck, none of the funds were able to yield a positive alpha. Andrikogiannopoulou and Papakonstantinou (2019) claimed that the methodology of Barras et al. (2010) underestimated the proportion of nonzero-alpha funds, making it overly conservative. Their concern was regarding statistical power, where FDR can alter its conclusion that most funds have zero alpha when applied in performance evaluation and other domains with low power. They claimed that the FDR approach is not likely to instigate substantial improvement over more straightforward methodologies. In settings with low signal-to-noise ratio, meaning consequently, individual tests have low power, meaning the FDR approach is rendered not relevant (Andrikogiannopoulou & Papakonstantinou, 2019)

Fama and French (2010) used Kosowski et al. (2006) bootstrap method and modified it. They examined U.S. mutual fund performance from 1984 until 2006. Fama and French (2010) findings contradicted Kosowski et al. (2006) as they did not find any evidence for an overperformance in the top 10% of U.S. mutual funds over this period. However, Fama and French (2010) support (Kosowski et al., 2006) findings on the bottom 10% of mutual funds are due to bad skill in the managers of these funds. Cuthbertson, Nitzsche, and O'Sullivan (2008) performed a study of U.K. mutual funds from 1975 until 2002 using the bootstrap method of Kosowski et al. (2006), they concluded the same as Kosowski et al. (2006). Specifically, they found indications of a lack of stock-picking abilities in the bottom funds and stock-picking skills in the top performers.

# 3 Methodology

The goal of this chapter is to provide our reader with the models that we will be using to evaluate performance of mutual fund managers. Furthermore, we will discuss the bootstrap method and how we use bootstrapping to distinguish between luck and skill. We operate under the null hypothesis of no true performance in individual funds. However, in any sample of a certain size, it is reasonable to expect an abnormal performance in the distribution tails, so separating luck from skill is a crucial element of our thesis.

## 3.1 Model Selection

In this thesis we will be using Jensen's alpha to evaluate the performance level of the mutual funds, ranked on their t-statistic of alpha. The abnormal performance Jensen (1968) will be calculated by doing a time series regression in R, calculated by taking excess return and deducting risk-free return, shown in the model below. The key is to differentiate the return based on skill and the return based on luck. In order to try to distinguish luck from skill in performance, we will implement the bootstrap approach of Kosowski et al. (2006).

### 3.1.1 Single-factor Model

In literature previously reviewed we have briefly discussed which models that have been used in the past studies. This will be a more specific description of the most used models. The single-factor model by Jensen (1968) is the core building block for all of the models discussed in this section. The single-factor model is based on the CAPM, showing us the relationship between risk and the return for an asset, based on its exposure to the market factor. Jensen altered the CAPM model and added another element, Jensen’s alpha. This is measurement of whether the asset would give an abnormal return, according to the theoretical CAPM. Positive alpha generates an overperformance according to CAPM, and a negative alpha indicates an underperformance. In a perfectly efficient market, alpha would be a neutral value; thus, it would disappear, i.e., equal to zero. The single-factor model is written as follows:

$$r_{j,t} = \alpha_j + \beta_j MKT + \varepsilon_t \tag{1}$$

In equation (1), $r_{j,t}$ is given as the excess return of asset $j$ in a month and MKT is the market excess return. The error term representing the market is given by $\varepsilon_t$, and has an expectation of zero representing the individual fund $i$’s specific risk, which is diversifiable but not explained by the market. Hence, after diversification we are only left with market risk. The beta ($\beta_i$) coefficient explains how much the asset will change depending on the market factor. The beta gives us an idea of how much the asset is sensitive to the changes in the market, and how that effects the return. Alpha is the intercept in this model representing the fund’s overall performance.

### 3.1.2 Fama-French Three-factor Model

In the 1980’s and 1990’ there was a growing debate about the single-factor model by Jensen (1968) was not a complete model for determining the return on assets Reinganum (1981) and Breeden, Gibbons, and Litzenberger (1989). Fama and French (1993) developed an extension on the single-factor model, by adding two additional factors, size factor (SMB) and value factor (HML). The way Fama and French (1993) constructed these factors was by dividing companies on the New York Stock Exchange (NYSE), American Stock Exchange (AMEX) and NASDAQ Stock Market into different portfolios. They divided the companies based on size and market value.

The SMB-factor is based on the companies' market value; specifically, the average portfolio returns holding a long position in companies with small (S) capitalization, minus the portfolio returns of large-capitalization companies (B). For the HML-factor, they divided companies into three groups based on their book-to-market value, high (H), medium (M) and low (L). This was a continuous process during all the years of their research from 1963 to 1993. They produce six portfolios (Small-High, Small-Medium, Small-Low, Big-High, Big-Medium and Big-Low), creating the baseline for the development of the SMB- and HML-factors. The formula for the SMB-factor is given in the equation below (2).

$$SMB = \left(\frac{1}{3}SH + \frac{1}{3}SM + \frac{1}{3}SL\right) - \left(\frac{1}{3}BH + \frac{1}{3}BM + \frac{1}{3}BL\right) \tag{2}$$

The main purpose of the SMB-factor is to account for companies with a low market value and their returns compared to companies with a high market value. Bauman and Miller (1998) argues in their studies that small companies generate a higher return then big companies over time. The formula for the HML-factor is given in the equation below (3):

$$HML = \left(\frac{1}{2}SH + \frac{1}{2}BH\right) - \left(\frac{1}{2}SL + \frac{1}{2}BL\right) \tag{3}$$

The HML-factor is the average return of companies with high book-to-market ratio (value portfolios) subtracted the average return of companies with low book-to-market ratio (growth portfolios). Hence, a positive HML value indicates a higher return in the value portfolios compared to the growth portfolios. The full equation for Fama-French three-factor model is stated in the equation below (4).

$$r_{j,t} = \alpha + \beta_j MKT_t + \beta_2 SMB_t + \beta_3 HML_t + \varepsilon_{j,t} \tag{4}$$

### 3.1.3 Carhart Four-factor Model

Carhart (1997) further developed the Fama and French (1993) three-factor model by adding a momentum factor (PR1YR). This momentum factor is based on the studies of Jegadeesh and Titman (1993). The goal of this factor is to capture the one-year momentum anomaly. Specifically, this factor accounts for stocks that has increased (decreased) in value will continue increasing or decreasing in the next period. Within the time frame of one year, as discussed earlier in the literature review. When Carhart (1997) generated this factor, he takes a portfolio of the best performing stocks and subtracts that with a portfolio of the worst performing stocks, creating the momentum effect (PR1YR)[1].

$$r_{j,t} = \alpha + \beta_j MKT_t + \beta_2 SMB_t + \beta_3 HML_t + \beta_4 PR1YR_t + \varepsilon_{j,t} \tag{5}$$

We will be using the four-factor model of Carhart (1997) as our main performance model as stated in equation (*5*). The four risk factors in Carhart's model cannot be diversified away; hence we need to take them into account. However, we will apply all the models, to illustrate the difference in results and compare them throughout our study.

We also implement a minimum number of twelve observations (N=12) in our sample. Kosowski et. al (2006) and Fama and French (2010) implemented a minimum of 36 and 8, leaving us to claim the middle position. Another reason for using this limit is that our sample would shrink by around 10% if we used a 36-observation minimum.

## 3.2 Bootstrap

Bootstrap method similar to Kosowski et al. (2006) is used in order to distinguish luck from skill in manager performance. This is the crucial element of our thesis, and this methodology is used to help us evaluate the statistical significance of our individual managers' performance correctly. It is arduous to evaluate significance of the observed performance using a parametric test due to the intricate dependencies in the cross-section and the non-normal returns. The bootstrap procedure is a joint test instead of an individual parametric test. It relies on fewer assumptions as it is robust to any dependencies in the cross-section, allows general distributional characteristics, and automatically takes sampling uncertainty into account (Yan et al. 2015). Following our bootstrap tests, we have provided the parametric in addition to bootstrapped p-values in the following tables and figures to illustrate the difference in results. Kosowski et al. (2006) implies the benefits of using bootstrap accurate inference when the sample size is limited and/or few observations. Considering the limited amount of funds available in the Norwegian market compared to the U.S., it makes the bootstrap method vital for our research and analysis of Norwegian mutual funds.

[1]For more detailed explanation see Fama and French (1993) and Jegadesh (1993).

Bootstrap is a cross-sectional methodology it precludes the necessary inference. In a traditional original square regression (OLS) one assumption is that residuals are normally distributed and there are several properties that may lead to the rejection of this assumption. In this thesis, we have been using Jensen's alpha as our performance evaluation measurement. It is easier to test for statistical significance in Jensen's alpha due to Sharpe-ratio failing to differentiate anomalies, meaning the results can be manipulated using Sharpe-ratio. Jensen's alpha is not without flaws, as differentiating between luck and skill is not always possible, but this is one of the areas we will examine further in our thesis. Studying the cross-section on mutual fund alphas possible non-normalities will be included as well as for individual funds.

Looking at the reasoning behind these properties, one is that the skewness and kurtosis of mutual funds tend to differ from normal distribution (Kosowski et al., 2006). Fund managers normally hold big positions in a few stocks. This leads to the breach of the central limit theorem, where a significant equally weighted portfolio of non-normal distributed stocks would approach normality leaving standard parametric test-statistics invalid. The second property is individual stocks tend to have heteroscedastic variance in addition to exhibiting various levels of serial correlation in returns. The last point is investment strategies, where mutual fund managers may vary between investment strategies and alter their risk preferences. The risk may change due to their performance compared to similar portfolios or to overall market portfolio changes Kosowski et al. (2006). Each mentioned property can affect the sample and attribute to non-normality of mutual fund alphas resulting in normality being an indigent approximation. Considering the performance distribution in our data set the skewness and kurtosis are increasingly higher the further from center you get. When using the Carhart (1997) four-factor model the normality of residuals in our sample is revealed to be rejected for 74.77% of the mutual funds using Jarque-Bera test at a 5% significance level.

As bootstrap does not rely on any distributional assumptions it can improve the validity of the inference about performance significantly. It is widely argued that the bootstrap provides more definite assessment of the alpha estimates significance (Bickel & Freedman, 1984; Fama & French, 2010; Hall & Martin, 1988; Horowitz, 2003; Kosowski et al., 2006). Horowitz (2003) illustrated the effect of bootstrap in a Monte Carlo experiment resulting in significant reduction between the true and nominal probability of correctly rejecting the null hypothesis. E.g. the standard parametric t-test rejects abnormal performance less frequently than the bootstrap. One reason for this is that the bootstrap recognizes the existence of thick tails in individual fund returns.

The cross-sectional distribution of mutual fund residuals consists of a variety of individual fund distributions and disables the assumption of normality. These funds are identified by (1) heterogeneous risk-taking inn all funds and (2) and increased momentum in individual fund residuals. Despite normally distributed individual fund residuals this does not automatically indicate that the cross-sectional distribution of the residuals is normal. Considering all mentioned factors and given the intricacy of the joint distribution of the 107 mutual funds in the data set the bootstrap method is the most fitting method to apply. The primary intention of the bootstrap is instead of relying on parametric assumptions of e.g. normality, we estimate the statistical distribution of interest in order to properly infer. The estimation is done by resampling with replacement and generate the statistic of each resample.

### 3.2.1 Bootstrap Implementation

Under the premise of a null hypothesis of no true performance in individual funds we follow the method of Kosowski et al. (2006). The basis of the bootstrap is laid on the computation ordinary least squares (OLS) regression built on Carhart (1997) four-factor model. The OLS-estimates of residuals, factors loadings and alphas for fund *i* is given by:

$$r_{i,t} = \hat{\alpha}_i + \hat{\beta}_{1i}MKT_t + \hat{\beta}_{2i}SMB_t + \hat{\beta}_{3i}HML_t + \hat{\beta}_{4i}PR1YR_t + \hat{\varepsilon}^b_{i,t_\epsilon} \tag{6}$$

The following are preserved for fund *i*: The coefficient estimates: $\hat{\alpha}_i, \hat{\beta}_{1i}, \hat{\beta}_{2i}, \hat{\beta}_{4i}$; the time-series estimated residuals: $\{\hat{\varepsilon}^b_{i,t_\epsilon},\ t = T_{i0}, \dots, T_{i1}\}$, where the dates for the first and last month are given by $T_{i0}$ and $T_{i1}$, respectively; and the t-statistic of alpha: $\hat{t}_{\hat{\alpha}_i}$ . Next step is to construct the pseudo-random time-series of resampled residuals. This is depleted by drawing random sample with replacement from the residuals of fund *i*. This is also required to have the same length as the original sample.

The length is given as follows: $\{\hat{\varepsilon}^b_{i,t_\varepsilon}, t_\varepsilon = S^b_{T_{i0},\dots,T_{i1}}\}$. *b* is the bootstrap iteration and *T* defines start end endpoint. By implementing the fitted values already retrieved we combine these with the time-series of resample residuals. This constructs the pseudo-monthly time-series of excess returns for fund *i* and inflict the null of no outperformance. The null hypothesis, no true performance in individual funds, is illustrated by $\alpha_i = 0$ or equivalently a time-series of an artificial return represented by $\hat{t}_{\hat{\alpha}_i} = 0$. This is designed to have a true performance equal to zero, nonetheless when regressed in the four-factor model it may result in a non-zero estimate of alpha. This may also include the t-statistic and depends on the drawn residuals in the bootstrap. The Carhart (1997) four-factor model is estimated based on the pseudo excess return vector. A positive (negative) alpha may be the result of an atypical high number of positive (negative) residuals provided by the bootstrap sample, illustrated by the *b'*s in the equation below. The null of no true performance is imposed as $\alpha_i = 0$ and $\tilde{\varepsilon}^b_{i,t,}$ is given as the sampling variation (7).

$$r^b_{i,j} = \alpha_i \, \hat{\beta}_{1i} MKT_t + \hat{\beta}_{2i} SMB_t + \hat{\beta}_{3i} HML_t + \hat{\beta}_{4i} PR1YR_t + \tilde{\varepsilon}^b_{i,t,} \qquad (7)$$

The equation, time-series of artificial returns, is constructed to have no true performance. As bootstrap process in this thesis is repeated 10,000 times, we may obtain a non-zero estimated alpha for a random bootstrap *b*. When the artificial returns are regressed on the Carhart (1997) four-factor model, it may occur that for a given bootstrap sample *b* an abnormal amount of positive (negative) alphas may be drawn as a result of the sampling variation surrounding the zero true performance and the drawn residuals.

The next step is to build the cross-section of bootstrapped alphas for all funds (*i=1, 2, …, 107*), by repeating the steps above for all iterations of the bootstrap (*b=1, 2,…, 10,000*). The bootstrapped t-statistics of alphas $\tilde{t}_{\hat{\alpha}_i}$ are, across all bootstrap iterations, ordered from lowest ($\tilde{\alpha}^b_{min}$ ) to highest ($\tilde{\alpha}^b_{max}$), creating a B × M matrix. B contains rows from 1 to N, where the lowest bootstrapped values are held in row 1 while the highest values are held in row N. Each of the ex-post ranked funds are represented in the matrix, which represent the funds' luck distributions. The same sorting procedure is also performed for the t-statistic ($\tilde{t}^b_{\tilde{\alpha}_i}$) before comparing its respective luck distribution given as $f\left(\tilde{\alpha}^b_i\right)$, enabling us to separate luck from skill. If we look at e.g. the distribution of the alphas in the top performing fund, we compare the its luck distribution with the ex-post performance alpha. To determine whether superior skill exist the bootstrap simulations need to engender more extreme positive (negative) alphas compared to the actual observed alpha at a significance level of 5%.

We consider both estimated t-statistic of alpha and estimated alpha. The t-statistic of alpha has a superior predictive ability as a sorting term when comparing performance under the assumption of no true performance, $\alpha_i = 0$. The estimated alpha is argued to be lacking in rigor it has been argued that t-statistic is more precise (Busse, Goyal, & Wahal, 2010; Fama & French, 2010; Kosowski et al., 2006). Mutual funds with a short lifespan characterized with high risk-taking will have a greater variance estimated alpha distribution and generate specious outliers in the cross-section, and the t-statistic addresses this issue. Following these arguments, in many of our bootstrap test in this thesis we will be focusing on the t-statistic of alpha, rather than alpha.

### 3.2.2 Bootstrap Extensions

Some extensions to the bootstrap procedure are made on the basis of the assumption of independent residuals. Both possibilities of autocorrelated residuals and factor returns are addressed, in addition to allowing residuals being cross-correlated and factor returns, and residuals being correlated (Fama and French, 2010). We apply several bootstrap extensions in order to test the robustness of our bootstrap results. Firstly, we run a stationary bootstrap (Politis & Romano, 1994) by resample the return residuals in data blocks. Secondly, we examine whether our results are impacted by autocorrelation in factor returns. Thirdly, we investigate the impact of cross-correlation between fund residuals. In the fourth extension we constructed portfolios of funds where we considered the corresponding average statistics on each tail of the portfolios to determine whether cross-sectional individual fund alpha analysis is affecting our inference tests. Lastly, we examined whether the length of our data impacted our results by imposing different minimal amounts of observations. All of this will be closely examined and discussed in more depth in section 5.3 Sensitivity Analysis.

# 4 Data

The data section presents the data used to evaluate the performance of the Norwegian mutual funds in our sample. The data review makes up the basis for the empirical analysis performed in chapter 5.

## 4.1 Sample Mutual Funds

The dataset comprises of 107 actively managed Norwegian mutual funds, both surviving and non-surviving, at Oslo Stock exchange between 1987 and 2019. Funds pursuing neutral investment strategies (passively managed/index funds), we have omitted. Restriction made to our sample is that each of these funds has a minimum of 80% domestic equities. The period is selected based on the availability of sufficient market information on both stock and benchmark. As we followed Ødegaard (2019b) argument constructing the risk-free rate based on the one-month Norwegian Interbank Offered Rate (NIBOR) as the interest rate proxy, we chose to start the period in 1987 to maintain consistency. The market benchmark is obtained from the Norwegian equity market. The restriction to only include Norwegian funds is made to safeguard the consistency in the thesis. The risk exposure varies from market to market, and the limit enables the use of only one benchmark.

We have obtained historical fund data from the TITLON database, providing complete daily information on all fund's Net Asset Value (NAV) throughout the period. NAV represents a fund's per-share market value. Using an adjusted NAV deducting ongoing costs such as management fees, we have calculated the net return of each fund, divided by the number of outstanding shares. The Nav is adjusted for dividends and other events affecting value. TITLON provides daily data, and we have constructed each funds' monthly return using the last reported NAV each month. The NAV and return of fund *i* is given at time *t* as providing the net of cost one-month simple return between period *t* and *t-1* is given as follows:

$$r_{i,t} = \frac{NAV_t - NAV_{t-1}}{NAV_{t-1}} \tag{8}$$

The sample fund's average lifetime is approx. 13.6 years and in Appendix A, Table A.I., it is displayed the number of funds available in the thesis. The table provides various descriptive statistics such as number of observations, mean return net of cost and standard deviation. Each fund is given the same importance by weighing them equally regardless of size, enabling us to consider each fund evenly.

In the Norwegian fund market, all funds are domestic open-end equity funds meaning that fund shares may be redeemed or issued at will without limitations. Figure 1 is a depiction of the mutual fund market for the period 2003-2019. It illustrates the number of customer relationships and total assets managed in the period. The number of customer relationships has held a small growth over the years, as it has grown from 695.077 in 2003 to 1.027.725 in 2019. At the same time, total assets managed display rapid growth, from approx. 38 MNOK in 2003 to 677 MNOK in 2019. It was a decline in 2008, most likely due to the global recession; however, the mutual fund market seems to have had an extensive growth during 2003-2019.

**Figure 1: Number of Customer Relationships versus Total Assets Managed**

The figure reports the number of customer relationships (blue line) and total assets managed (red line) in the period 2003-2019[2]. Note that the number of customer relationships is not the same as the number of customers, as the same customer may hold shares in more than one fund. One customer relationship may function as a nominee with an unknown number of customers. Total assets managed are all assets managed in the Norwegian mutual fund market. Both are reported as a logarithmic scale to illustrate the development during this period.

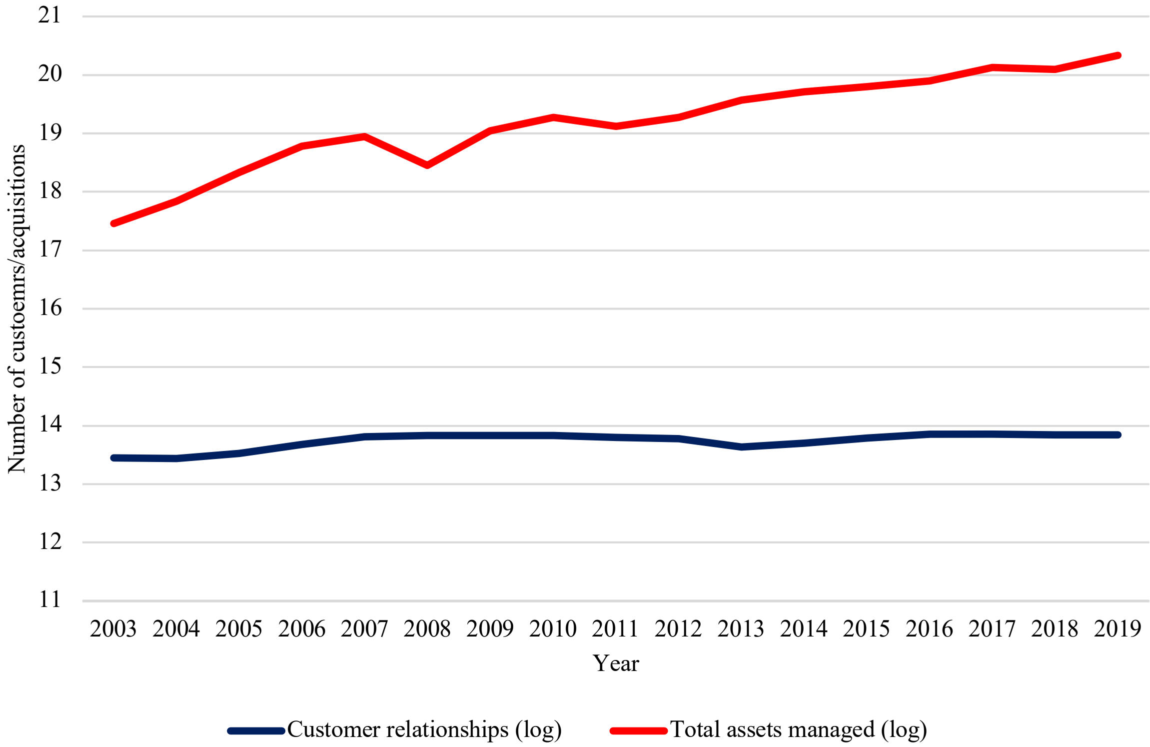



Table 1 reports the same period as Figure 1, 2003-2019. The table consists of descriptive data on the Norwegian mutual fund market. Column 2 reports the customer relationships showing an increase from 2003 until 2010 before stabilizing around one million. The total assets managed, column three, has had a steady growth for most of the period except, e.g. 2008 (the great recession). As the number of customer relationships only has a small increase, as opposed to the steep growth in total assets under management, the assets per customer relationships have increased from 55.000 to 659.000 NOK, indicating that the Norwegian mutual fund market is increasingly attractive to larger and larger investors.

[2] Provided by the Norwegian Mutual Fund Association (Verdipapirfondenes forening, VFF).

**Table 1: Norwegian Mutual Fund Market 2003-2019**

The table reports various descriptive statistics for the Norwegian mutual fund market in the period 2003-20192. Column 2 is the number of customer relationships. Note that customer relationships are not the same as the number of customers as the same customer may hold shares in more than one fund, and one customer relationship may function as a nominee with an unknown number of customers. Net fund acquisitions are the realization of funds minus redemption. Column three reports the total assets managed in MNOK each year. Column 4 is the total assets managed per customer relationship, while column five is the net fund acquisitions. Net fund acquisitions are the realization of funds minus redemption.

| Year | Customer relationships | Total assets managed | Assets per customer rel. | Net fund acquisitions |
|---|---|---|---|---|
| 2003 | 695,077 | 38,157,064 | 55 | 1,382,142 |
| 2004 | 685,471 | 55,848,744 | 81 | 4,463,194 |
| 2005 | 744,752 | 90,985,266 | 122 | 4,369,224 |
| 2006 | 867,063 | 143,022,019 | 165 | 8,796,835 |
| 2007 | 997,048 | 169,153,417 | 170 | 1,287,885 |
| 2008 | 1,014,421 | 103,270,488 | 102 | -261,664 |
| 2009 | 1,014,632 | 186,348,433 | 184 | 6,110,742 |
| 2010 | 1,010,613 | 234,208,646 | 232 | 9,632,590 |
| 2011 | 984,855 | 201,572,313 | 205 | -2,198,926 |
| 2012 | 958,980 | 235,193,711 | 245 | 3,400,331 |
| 2013 | 838,889 | 314,568,652 | 375 | 10,401,478 |
| 2014 | 889,704 | 364,817,630 | 410 | -10,751,326 |
| 2015 | 975,407 | 394,652,576 | 405 | -144,419 |
| 2016 | 1,033,733 | 438,083,274 | 424 | -412,309 |
| 2017 | 1,039,855 | 549,509,258 | 528 | -5,252,363 |
| 2018 | 1,027,725 | 533,403,911 | 519 | 4,480,095 |
| 2019 | 1,027,725 | 677,398,661 | 659 | 2,122,778 |

## 4.2 Interest Rate

Based on Net Asset Value, we calculated the one-month simple return for each fund, and to construct excess return, we deduct the risk-free interest rate. In economic literature, treasury bills are widely accepted, but our use of the Norwegian market (OSEBX) as our benchmark the liquidity of Norwegian treasury bonds is not sufficient compared to other more comprehensive markets. Ødegaard (2019b) argues using the Norwegian Interbank Offered Rate (NIBOR) as a more suitable proxy. NIBOR intends to function as a reflection of the interest rate of unsecured money market lending between banks. To avoid the use of imperfect proxies, we have limited our sample period from 1987 as the interest rate data between 1983 and 1986 are considered chaotic. According to Ødegaard's arguments, we use the one-month NIBOR rate to construct a risk-free monthly rate estimated as follows:

$$r_f = (1 + NIBOR)^{\frac{1}{2}} - 1 \tag{9}$$

In Appendix B, Figure B.I. the monthly overnight NIBOR rate is plotted for the full sample period 1987-2019.

## 4.3 The Market Proxy: Benchmark Index

To appropriately measure mutual fund performance, we need to establish a benchmark to represent market returns. An ideal would be the actual market portfolio, but as this is not genuinely measurable, we need a reasonable approximation. The most-traded shares listed on Oslo Stock Exchange make up the Oslo Stock Exchange Benchmark Index (OSEBX). However, as we are focusing on Norwegian mutual funds, the capped version Oslo Stock Exchange, Mutual Funds Index (OSEFX), is a natural benchmark. Complying with UCITS[3] directives and its design to meet diversification requirements is an accurate benchmark. The OSEFX originated in 1995, meaning it cannot function as a proxy between 1987 and 1995. In this thesis, we require only one benchmark for the whole period 1987-2019, and a widely used benchmark is the Oslo Stoch Exchange All-Share Index (OSEAX)[4]. OSEAX consists of all shares listed on Oslo Stoch Exchange and is adjusted for dividend payments and is adapted for corporate actions daily. The market proxy is an equally weighted portfolio constructed using most stock at the Oslo Stock Exchange and is restricted by filtering out the smallest and the least liquid stocks.

## 4.4 Risk Factors

Ødegaard (2019a) is providing data on the risk factors for the four-factor model based on empirical data from the Oslo Stock Exchange. We relied on Ødegaard's database to provide data on the market factor (MKT), Small-Minus-Big (SMB), High-Minus-Low (HML), and Momentum (PR1YR). SMB considers small capitalization companies' average return in an extended position minus big capitalization companies. HML consists of the average return on high book-to-market ratio portfolios minus low book-to-market ratios (value minus growth portfolios). PR1YR is read out as prior-one-year meaning portfolios consisting of the highest one-year lagged returns minus the lowest in a long position. In Appendix C all factor loadings are reported for each individual fund.

Figure 2 is a time-series plot illustrating the cumulative returns of the factor loadings for the entire sample period. Looking at the market-factor, it is highly volatile and producing

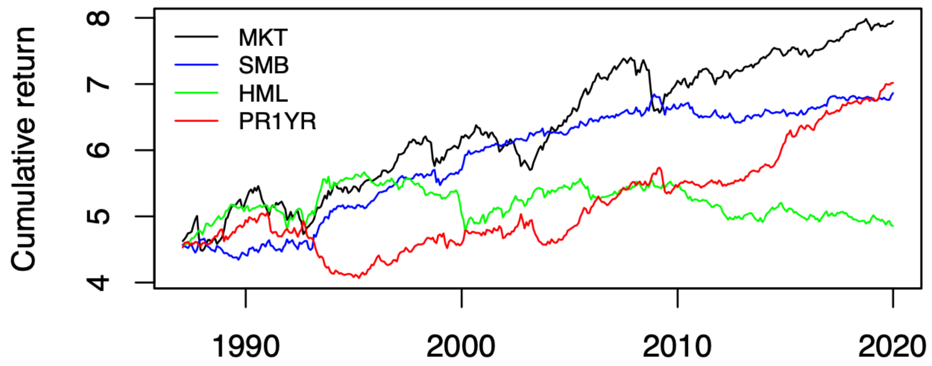
[3]UCITS: The Undertakings for Collective Investment in Transferable Securities Directive 2009/65/EC is a consolidated EU Directive

[4] Historical data on OSEAX is provided by Ødegaard (2019) and can also be found at Oslo Stock Exchange, publicly available market data.

the highest accumulated return. The SMB-factor is performing stably throughout until approximately 2010, where it stabilizes for the remaining period. The HML-factor reports high volatility through the mid-1990s until 2000, displaying the lowest accumulated return at the end of the period. The PR1YR-factor reports a drop in accumulated returns in the mid-1990s before steadily growing for the remaining period.

**Figure 2: Risk Factors Cumulative Return Loadings**

The cumulative factor returns in the Carhart four-factor model for the full period 1987-2019 is illustrated below. The figure illustrated the different impacts of the risk factors given in the logarithmic scale.




The risk factors are described further in Table 2, reporting various statistics for each factor for different periods: 1987-2019; 1987-1997; 1998-2008; 2009-2019. The mean returns described in Panel A, depict that the SMB-factor generates the highest mean return for the first and second periods. In contrast, for the third period, the PR1YR-factor provides the highest mean return of 13.579%. The SMB-factor is experiencing a significant drop in the third period reporting only 1.268% after being the highest for the first two. The HML-factor had a steep decline in performance through the periods with a negative return of -4.764% in the third period. The opposite is noted for the PR1YR-factor reporting low performance of only 1.272% in the first period growing to 13.579% in the third period. The standard deviations in Panel B are quite similar to each other, all reporting a steep decline in the third period compared to the first two. The HML-factor is experiencing the lowest standard deviation recorded of 11.494% in the third period.

Panel C reports the maximum, and minimum factor returns saying that the first period has the highest return for the MKT-, SMB- and HML-factor of 16.506%, 22.140% and 14.661% respectively, while for the PR1YR-factor the second period is reporting its highest return of 15.427%. The market- and the PR1YR-factor has its lowest return in the first period, as opposed to the SMB- and HML-factors reporting its lowest returns in the second period. Panel D reports the correlation matrix for the risk factors. The correlation between the factors is relatively low, except for the negative correlation between the market- and SMB-factor of -0.448.

**Table 2: Factor Returns Descriptive Statistics**

This table illustrates different descriptive statistics of the risk factors in four different periods in our sample: 1987-2019; 1987-1997; 1998-2008; 2009-2019. All are eleven-year periods reporting the annualized mean returns (Panel A), standard deviation (Panel B), and the max (min; Panel C) of each factor in percent. Panel D reports the factor correlation matric of each risk factor.

| | MKT | SMB | HML | PR1YR |
|---|---|---|---|---|
| **Panel A: Mean factor returns** | | | | |
| Jan 1987-Dec2019 | 7.094 | 7.853 | 2.079 | 8.674 |
| Jan 1987-Dec 1997 | 7.263 | 10.418 | 9.790 | 1.272 |
| Jan 1998-Dec 2008 | 2.428 | 11.874 | 1.213 | 11.170 |
| Jan 2009-Dec 2019 | 11.591 | 1.268 | -4.764 | 13.579 |
| **Panel B: Standard Deviation** | | | | |
| Jan 1987-Dec2019 | 20.736 | 14.159 | 16.177 | 16.305 |
| Jan 1987-Dec 1997 | 22.741 | 15.755 | 18.199 | 17.234 |
| Jan 1998-Dec 2008 | 24.178 | 14.239 | 17.798 | 17.559 |
| Jan 2009-Dec 2019 | 13.829 | 12.165 | 11.494 | 13.755 |
| **Panel C: Max (min) factor returns** | | | | |
| Jan 1987-Dec2019 | 16.506 (-28.686) | 22.140 (-17.078) | 14.661 (-16.649) | 15.427 (-16.781) |
| Jan 1987-Dec 1997 | 16.506 (-28.686) | 22.140 (-10.460) | 14.661 (-15.717) | 13.502 (-16.781) |
| Jan 1998-Dec 2008 | 11.809 (-24.577) | 13.274 (-17.078) | 9.325 (-16.649) | 15.427 (-14.219) |
| Jan 2009-Dec 2019 | 14.876 (-9.039) | 12.550 (-11.030) | 6.865 (-7.420) | 12.052 (-16.095) |
| **Panel D: Factor correlation matrix** | | | | |
| MKT | 1 | | | |
| SMB | -0.448 | 1 | | |
| HML | 0.051 | -0.138 | 1 | |
| PR1YR | -0.157 | 0.105 | -0.118 | 1 |

## 4.5 Mutual Fund Returns: Potential Biases

The production of biased results has been indicated as a possibility in previous studies. The most obvious bias is the survivorship bias that occurs if non-surviving funds are left out (Brown, Goetzmann, Ibbotson, & Ross, 1992). When liquidated funds are removed from the data sample, survivorship bias can occur as a property of the sample selection. Non-surviving funds follow a strategy that has been confirmed failing, and by excluding these funds, the approach is also eliminated (Elton et al., 1996). These funds are primarily not liquidated because of poor one-year performance but rather for multiple-year underperformance (Carpenter & Lynch, 1999). Funds that yield a high return and persistently perform tend to survive, resulting in the sample's average return being upward-biased. The aggregate performance will then be artificially high, leaving our sample results incomplete. Carpenter and Lynch (1999) also introduce a look-ahead bias and address the importance of year-end returns. Look-ahead bias might occur when a fund is required to exist over a certain period and might occur when a fund has a too-short lifetime. In addition to poor performance, the other main reason for a fund to be dissolved is that the cost of maintaining the fund surpasses the profits, but this may be due to the fund not performing. Our data set contains both non-surviving and surviving funds to generate the most accurate results. We have introduced the condition of 12 observations but not any regarding fund size, also in assuming that in cases of merged funds, the money is invested in the acquiring fund (Elton et al., 1996).

Table 3 provides various descriptive data of the market proxy and equally weighted portfolios of all funds, surviving funds, and non-surviving funds in our sample reported for different periods: 1987-2019; 1987-1997; 1998-2008; 2009-2019. Panel A, detailing the entire sample period, states that all portfolios outperformed the market proxy looking at mean return with the OSEAX proxy reporting a mean return of 12.378%. Looking at the maximum and minimum performance each of the portfolios of sample funds (all; alive; dead) are reporting its highest performance in the first period (Panel B) and their lowest in the second period (Panel C).

**Table 3: Benchmark and Fund Returns Summary Statistics**

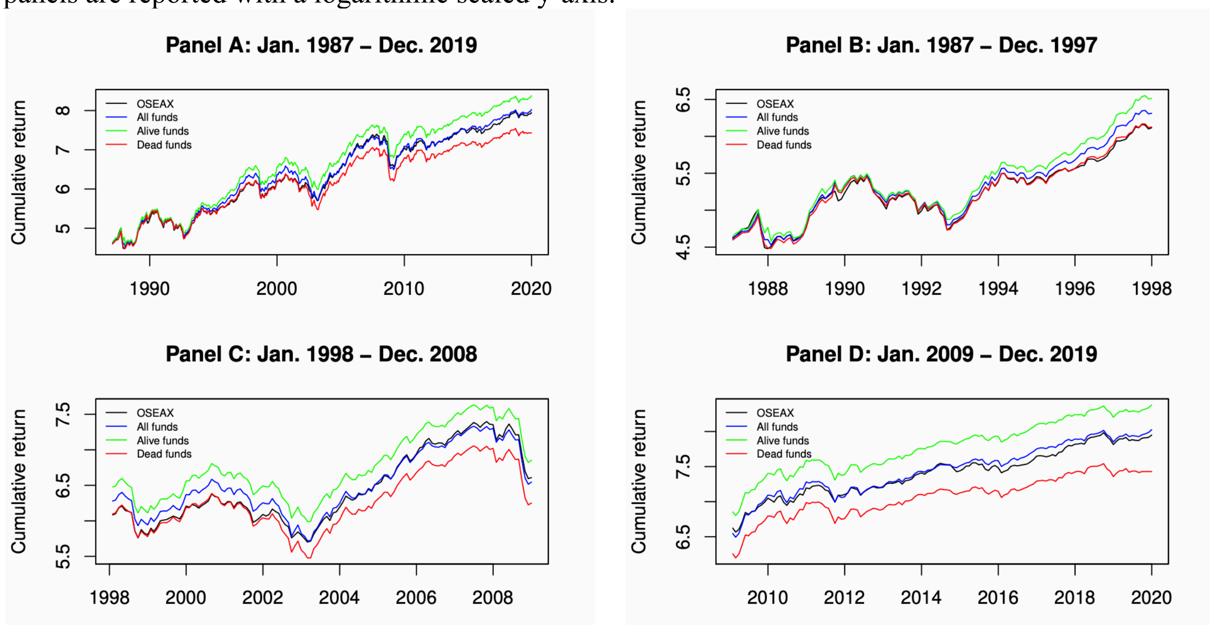
The table reports various descriptive data statistics in equally weighted portfolios consisting of the OSEAX, all funds in the sample, the surviving fund (alive), and non-surviving funds (dead). Column one and two reporting mean returns, and standard deviations are annualized, while columns five and six are reporting the monthly maximum and minimum. Column three and four report the kurtosis and skewness of each portfolio. All numbers are in percent and reported for different periods in time; 1987-2019; 1987-1997; 1998-2008; 2009-2019.

| | Mean return | Standard deviation | Kurt | Skew | Max | Min |
|---|---|---|---|---|---|---|
| **Panel A: 1987-2019** | | | | | | |
| OSEAX | 12.378 | 20.618 | 2.807 | -0.983 | 17.445 | -27.423 |
| All | 12.597 | 20.635 | 2.087 | -0.809 | 17.546 | -25.277 |
| Alive | 13.709 | 20.808 | 2.017 | -0.790 | 18.648 | -25.391 |
| Dead | 10.833 | 20.889 | 2.125 | -0.789 | 18.145 | -25.088 |
| **Panel B: 1987-1997** | | | | | | |
| OSEAX | 16.459 | 22.620 | 2.538 | -1.049 | 17.445 | -27.423 |
| All | 17.848 | 21.066 | 0.895 | -0.565 | 17.546 | -19.560 |
| Alive | 19.813 | 21.534 | 0.768 | -0.592 | 18.648 | -17.031 |
| Dead | 16.225 | 21.395 | 1.329 | -0.594 | 18.145 | -21.477 |
| **Panel C: 1998-2008** | | | | | | |
| OSEAX | 7.489 | 23.990 | 1.612 | -0.973 | 12.489 | -23.934 |
| All | 5.378 | 24.934 | 1.360 | -0.940 | 13.821 | -25.277 |
| Alive | 6.363 | 24.993 | 1.376 | -0.911 | 16.112 | -25.391 |
| Dead | 4.407 | 25.024 | 1.356 | -0.946 | 14.102 | -25.088 |
| **Panel D: 2009-2019** | | | | | | |
| OSEAX | 13.185 | 13.827 | 0.855 | 0.085 | 15.047 | -8.841 |
| All | 14.566 | 14.540 | 1.528 | 0.016 | 15.541 | -10.401 |
| Alive | 14.951 | 14.468 | 1.541 | 0.029 | 15.616 | -10.324 |
| Dead | 11.868 | 15.026 | 1.293 | 0.061 | 15.417 | -10.581 |

Figure 3 shows an equally weighted portfolio illustrating the cumulative returns of all funds, OSEAX and surviving and non-surviving funds. The figure divided into four panels illustrating different periods, each consisting of eleven years. Studying the full sample period 1987-2019 in Panel A, the alive funds generate the highest cumulative return every year and have a steep incline from 2010 and throughout the sample period. The non-surviving funds are outperformed by both the market and surviving funds for all periods quite substantially. Especially through the second and third periods, the non-surviving funds are displaying significantly lower performance, oppose to surviving funds, which outperformed the market through all periods, and experienced a steep increase in the third period. Still, it is worth pointing out that in Panel B, the dead funds display a very similar pattern as the market for the full decade 1987-1997, especially after 1990. By eliminating non-surviving funds, it is a significant chance of imposing survivorship bias, which underlines the importance of including non-surviving funds.

**Figure 3: Cumulative Returns**

As of the figure, the graphs depict the cumulative returns of the market (OSEAX) and equally weighted portfolios consisting of all, dead and alive funds for different periods in time. Panel A illustrates the full period 1987-2019, while Panel B-D depicts different periods 1987-1997; 1998-2008; 2009-2019. All panels are reported with a logarithmic scaled y-axis.



# 5 Empirical Results

In the following chapter, we will be delving into our findings in our empirical analysis of Norwegian mutual fund performance. Firstly, we investigated our results on aggregate performance level using Jensen (1968) single-factor model, Fama and French (1993) three-factor model, and Carhart (1997) four-factor model. Our main emphasis will be on Carhart (1997), although we include the other models for comparison. Concluding this chapter, we will be examining our bootstrap results to determine if skilled or unskilled managers exist in our sample.

## 5.1 Aggregate Fund Performance

Table 4 reports our regression analysis results for the equally weighted portfolio on the aggregate level using all three performance models. Under the assumption of true alpha equal to zero, we focus on whether the funds can yield a positive alpha. Specifically, how the return depends on the exposure to the risk factors in each of the models. In Panel A, we can see that CAPM generated an alpha of 0.50% over the entire sample period. Fama-French generated an alpha of -0.38%, while Carhart generated an alpha of 0.04%. However, none of them are statistically significant. The essence of this is that no Norwegian mutual fund can produce superior significant abnormal returns on the aggregate level, with any of the models presented in this thesis over the entire sample period. We can see a decline in the alpha value from the single-factor model compared to the three-factor model. However, we experience a slight growth in alpha in the four-factor model, meaning that adding the momentum-factor increases the alpha value over the whole sample period. Over the period 1998-2008, we experienced a significant alpha for the 1998-2008 period at the 5% level, indicating a lack of managerial skill in this period. When we examined the factor loadings over the entire period, we can see that the market-factor is the most impactful and significant. Furthermore, the SMB-factor is less impactful, but also significant at a 1% level. The HML-factor is significant at the 1% level for the full period 1987-2019 and the second period 1998-2008, reported in Panels A and C, respectively. We experience a similar trend with the PR1YR-variable, being significant over the entire sample period at a 5% level of significance, but only in the one subperiod 1998-2008. From this, we can conclude that Carhart's (1997) four-factor model gives us significant values over the whole sample period and is the preferred model.

**Table 4: Equally Weighted Portfolio Alphas and Factor Loadings**

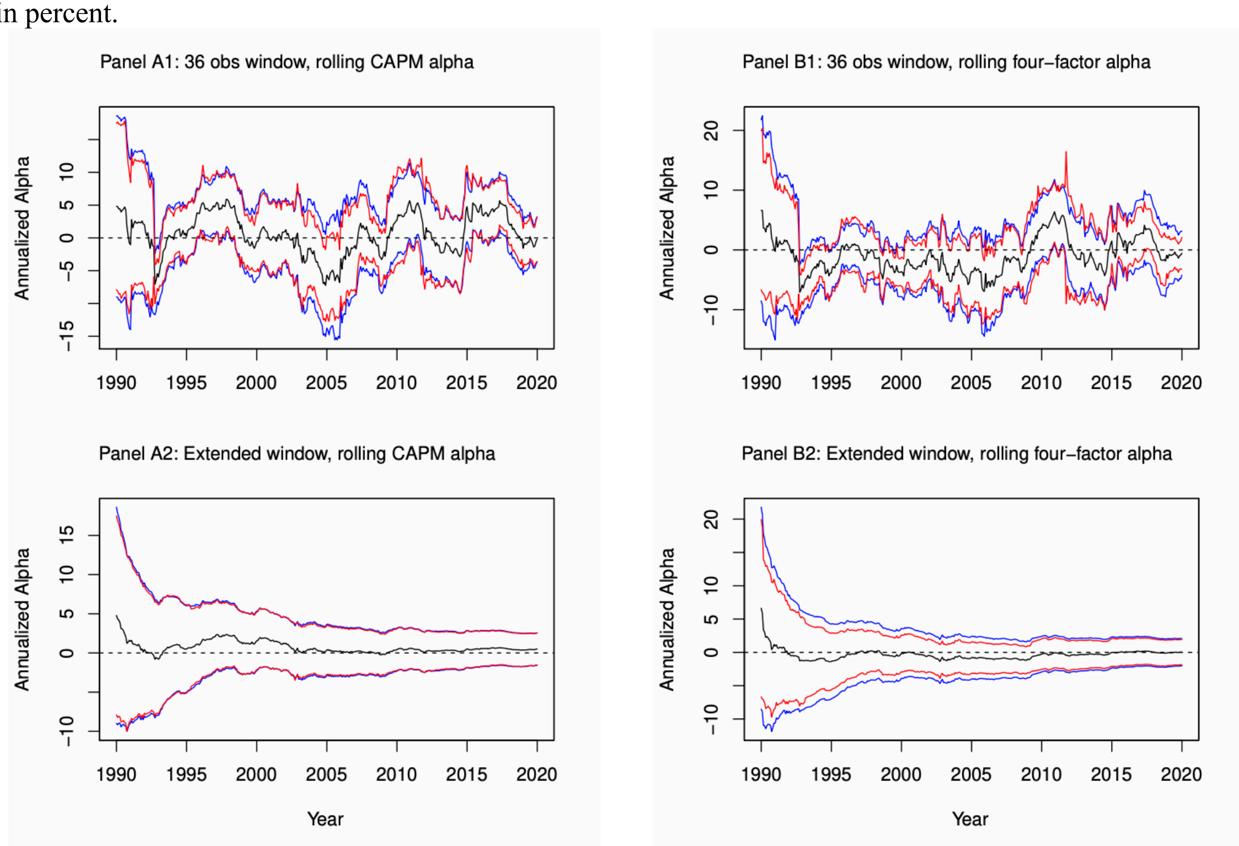
The table displays alpha, factor loadings, and adjusted R square for an equally weighted portfolio based on Norwegian mutual funds of our full sample over the entire period 1987-2019. Here we have the single-factor (CAPM), three-factor (FF), and four-factor (Carhart). Panel A provides us with the full sample. Panel B-D provides us with the sample divided into equal sub-periods of time. T-statistic for all the calculations are shown in the parentheses. The stars, *, ** and *** represent the statistical significance, 10%, 5% and 1% respectively. Alphas are annualized and in percent.

| Model | $\alpha$ | $\beta_{MKT}$ | $\beta_{SMB}$ | $\beta_{HML}$ | $\beta_{PR1YR}$ | $R^2_{adj}$ |
|---|---|---|---|---|---|---|
| **Panel A: Jan. 1987 – Dec. 2019** | | | | | | |
| CAPM | 0.50 | 0.96*** | | | | 0.92 |
| | (0.49) | (67.10) | | | | |
| Fama-French | -0.38 | 0.99*** | 0.10*** | −0.06*** | | 0.93 |
| | (-0.37) | (64.54) | (4.34) | (−3.39) | | |
| Carhart | 0.04 | 0.99*** | 0.10*** | −0.07*** | -0.04** | 0.93 |
| | (0.03) | (64.13) | (4.43) | (−3.66) | (-2.48) | |
| **Panel B: Jan. 1987 – Dec. 1997** | | | | | | |
| CAPM | 2.24 | 0.88*** | | | | 0.89 |
| | (1.06) | (32.85) | | | | |
| Fama-French | 0.22 | 0.91*** | 0.14*** | 0.03 | | 0.90 |
| | (0.10) | (30.94) | (3.38) | (0.91) | | |
| Carhart | 0.14 | 0.91*** | 0.14*** | 0.04 | 0.02 | 0.90 |
| | (0.06) | (30.87) | (3.37) | (1.03) | (0.63) | |
| **Panel C: Jan. 1998 – Dec. 2008** | | | | | | |
| CAPM | -2.14 | 1.01*** | | | | 0.95 |
| | (-1.25) | (49.19) | | | | |
| Fama-French | −3.49** | 1.03*** | 0.12*** | −0.11*** | | 0.96 |
| | (−2.17) | (47.86) | (3.45) | (−4.08) | | |
| Carhart | −2.45 | 1.02*** | 0.13*** | −0.11*** | −0.10*** | 0.96 |
| | (−1.60) | (50.43) | (4.04) | (−4.44) | (−4.29) | |
| **Panel D: Jan. 2009 – Dec. 2019** | | | | | | |
| CAPM | 1.31 | 1.01*** | | | | 0.91 |
| | (0.99) | (37.35) | | | | |
| Fama-French | 0.81 | 1.02*** | 0.03 | −0.05* | | 0.92 |
| | (0.60) | (32.15) | (0.90) | (−1.63) | | |
| Carhart | 0.78 | 1.02*** | 0.03 | −0.05 | 0.00 | 0.91 |
| | (0.54) | (30.32) | (0.90) | (−1.63) | (0.06) | |

To examine how alpha is evolving, we have in Figure 4 analyzed alpha in a rolling 36-month rolling window and an extended window. Specifically, both windows start at 36 months, where the rolling window goes from 1-36, 2-37,…, 360-396, while being calculated 1-36,1-37… 1-396 in the extended window. Figure 4 reports four panels containing both CAPM and the four-factor model estimations, using both window constraints. The lower windows plot the rolling window alpha estimates extending from 36 to 396 months, while the upper window length is 36 months. We have included a standard error and a Newey-West-corrected error bands to our observations. The solid line illustrates the annualized alpha estimates in percent in the full sample period between 1987 and 2019. Panels A is calculated using the CAPM Jensen (1968) single-factor model, and Panels B using the Carhart (1997) four-factor model.

**Figure 4: Equally Weighted Portfolio Estimates**

The figure reports the estimated alphas of equally-weighted portfolios of the sample funds illustrating the differences in the use of the capital asset pricing model (CAPM) and the four-factor model in different windows: 36 (Panel A1 and B1) and 396 (Panel A2 and B2). The black line reports the adjacent alphas while the standard errors are reported in blue, and Newey-West-corrected to standard error bands are reported in red. The CAPM estimates are reported in Panels A, while the four-factor estimates are reported in panels B. The alphas are annualized and reported in percent.




Examining the graphs, we observed an alpha of approximately 5% yearly at the start of all the graphs. However, we can observe a much higher fluctuation in alpha estimations in the 36 observational windows (Panels A1 and B1). We controlled the results with normal standard errors (Blue), and Newey-West corrected standard errors (Red). Specifically, in Panel A1, we observed the rolling CAPM alpha with a 36-observation window, calculated using Jensen (1968) single-factor model. Our calculations show that the alpha fluctuates, but we can observe that the changes are mostly positive over the broader part of the period. One can observe the alpha hover around zero, spiking and dropping seemingly arbitrary as of the panel. In Panel B1, where we observed the CAPM alpha in a rolling 36-month window calculated using the Carhart (1997) four-factor model, the alpha is mostly negative over the entire sample period. We see a steep increase before 2010, which can be explained by the rise in stock prices after the financial crisis. However, the alpha is also very close to dipping below zero at the end of the period. We experienced much less variation in the alpha values in Panel B1 compared to Panel A1. This is caused by the mutual funds being impacted by more factors in the Carhart (1997) model than the CAPM. When we applied the CAPM model, alpha was mostly positive over the entire sample period and ended up with a positive value at the end of our sample.

Panel B2 reports differing results from Panel A2. Here we applied an extended estimation with Carhart (1997) four-factor model, and when additional factors were included, the alphas seem slightly more stable yet not significant. The Panels B do not report the same number of spikes as in the CAPM model of Panels A, but the chart bottoms out in the same areas with approximately the same values. We observed a mostly negative alpha over the entire sample period for panel B, and at the end, alpha is close to zero. More accurately, the alpha hovers around zero in both the extended windows at the end of our period. For both Panels A2 and B2, the alpha began close to 5% in 1987 and rapidly dropped until 1993. The alpha retrieved positive values in the mid-1990s, and for Panel A2, it stabilized around zero for the reaming period. For Panel B, the negative alpha continued before level out around zero in the early 2010s. We can see a clear difference in the various approaches, whether it is rolling or extended, or Jensen/Carhart. In general, we see a smaller variance in the extended window, and the Carhart four-factor model has a lower alpha value then Jensen. This is related to the exposure to multiple factors, most notably the SMB-factor. As seen from the aggregate table, the SMB-factor is the most impactful of Carhart's factors (excluding MKT), explaining some of the drop in performance (alpha).

The results provide evidence of fund managers on aggregate do not create statistically significant positive returns net of cost, reporting a lack of sufficient stock-picking skill. Neither model provide sufficient evidence that fund managers do much else than collect fees. The results also show that we have an alpha with less variance in our extended window and follow the same trend as the previous graphs. Studying fund performers on an aggregate level does not exclude the possibility that individual fund managers inhabit superior or inferior skills. To examine the mutual funds on an individual level, we have in the next subsection adopted the bootstrap method of Kosowski et al. (2006).5.2 Performance - Lucky or Skilled

In the previous subsection, we have been looking at fund performance on the aggregate level without discovering a significant alpha at the 1% level. We will be examining the managers on an individual level, with the primary objective to distinguish skill from luck, attempting to identify whether there are skilled or unskilled managers. On the aggregate level, the unskilled managers may be lowering the alpha, proving unfavorable for the skilled managers.

## 5.2 Performance - Lucky or Skilled

In the previous subsection, we have been looking at fund performance on the aggregate level without discovering a significant alpha at the 1% level. We will be examining the managers on an individual level, with the primary objective to distinguish luck from skill, attempting to identify whether there are skilled or unskilled managers. On the aggregate level, the unskilled managers may be lowering the alpha, proving unfavorable for the skilled managers.

### 5.2.1 Bootstrap Evidence

The focus of this paper will now shift to the individual manager. Specifically, we will be examining if the individual manager inhabits stock-picking skill. Statistically, in any sizable sample, we will find funds that perform above and below the standard. We considered which of these funds' performance specifically are due to luck or actual skill. To distinguish between luck and skill, we will be utilizing the bootstrap method by Kosowski et al. (2006). The main goal is to search for statistically significant alphas in any of our mutual funds individually. In Table 5, we have provided selected results from a parametric t-test and the bootstrapped results. In Appendix D, the same parameters are reported for each individual fund. We divided into two separate measurements, alpha and t-alpha (t-statistic of alpha), to easily visualize the differences. The key feature being the difference between bootstrapped p-values and parametric p-values. We have chosen to divide into various points and percentiles among the bottom and top performers. More specifically, the table reports the three top-performing funds, followed by the top-five and -ten percentiles in the right tail. The same points and percentiles are also reported for the worst-performing funds. Row 1 reports the alpha associated with the given funds. Row 2 reports the bootstrapped p-value, and row 3 is the parametric p-value. In the next panel, instead of alpha, report the t-alpha for comparison. Starting with Panel A, where the funds are ranked using alpha, we observed a yearly alpha of 10.95% in the top-performing fund; however, it is not statistically significant for the bootstrapped p-value (0.54). All our top-performing funds follow the same trend with non-significant alphas, even when considering the top 10%, following the same pattern as previous research of observing non-significant alphas in the top performers. The second-best performing fund has a bootstrapped p-value of 0.11, generating interest as it is significantly lower than the top performers. Despite this, it remains insignificant and will not challenge the null hypothesis of no true performance; however, looking at parametric p-value as well, we cannot discard the performance based on luck alone. Moving to the left tail of the distribution, we observe significant alphas among the bottom performing funds. All worst performers in the table unveil a statistically significant alpha on a 5% level. The worst performing fund generated a yearly alpha of -19.06% with a p-value of 0.01, indicating evidence to reject the null hypothesis for the bottom performers. Also, the second-worst performing funds have p-value well within a 5% significance level (0.01). Continuing along the left tail looking at the bottom performing five and ten percentiles, we obtained statistically significant alphas at a 95% level of significance. At both the bottom five and ten percent, the p-values are 0.00 and 0.01. Based on this evidence, we do not observe evidence of skill in our top performers; thus, no evidence of rejecting the null for the superior performers. However, in our bottom performing funds, we find evidence that managers exhibit a lack of skill. The weakest performers are not merely unlucky. The sample provides evidence of a lack of skill, meaning we can reject the null of no true performance for the worst performers except for the bottom fund.

**Table 5: Bootstrapped Results**

The table provides cross-sectional bootstrapped results of all Norwegian Mutual funds in our sample for 1987-2019. Both panel's report on various percentiles and quintiles where Panel A provides four-factor alphas, and Panel B provides for-factor t-statistics of alpha. Column 1-5 displays the statistics of the bottom funds, while column 6-10 reports the top funds. Row 1 in Panel A reports the OLS estimate of alpha, where row 1 in Panel B reports the estimated t-statistic of alpha. Row 2 displays the cross-sectionally annualized associated alpha for the t-statistic, whereas row 3 displays the parametric p-values of the t-statistic. The statistics are based on 10,000 bootstrap resamples and are ranked on their t-statistic of alpha in both panels.

| | Bottom | 2nd | 3rd | Bottom 5% | Bottom 10% | Top 10% | Top 5% | 3rd | 2nd | Top |
|---|---|---|---|---|---|---|---|---|---|---|
| **Panel A: Fund Ranked on Four-Factor model Alphas** | | | | | | | | | | |
| Alpha | -19.06 | -18.62 | -16.93 | -11.89 | -7.01 | 3.02 | 5.38 | 6.18 | 7.62 | 10.95 |
| Bootstrapped p-value | 0.01 | 0.01 | 0.02 | 0.00 | 0.01 | 0.81 | 0.33 | 0.63 | 0.11 | 0.54 |
| Parametric p-value | 0.03 | 0.04 | 0.00 | 0.05 | 0.08 | 0.01 | 0.02 | 0.08 | 0.03 | 0.01 |
| **Panel B: Fund Ranked on t-statistic Four-Factor Model Alphas** | | | | | | | | | | |
| T-alpha | -3.22 | -3.18 | -2.96 | -2.45 | -1.73 | 1.19 | 1.94 | 2.15 | 2.19 | 2.23 |
| Bootstrapped p-value | 0.17 | 0.02 | 0.00 | 0.00 | 0.01 | 0.76 | 0.21 | 0.33 | 0.55 | 0.81 |
| Parametric p-value | 0.00 | 0.00 | 0.00 | 0.01 | 0.04 | 0.12 | 0.03 | 0.02 | 0.01 | 0.01 |

Panel B, ranking the funds on their t-statistic of alpha, displays much the same trends as Panel A as we do not observe statistically significant evidence among the top performers. In the top three, the lowest observed p-value is 0.33 in the third-best performing fund, which is an abrupt drop from 0.63 in Panel A. The top 5% performing fund is the one closest in obtaining a significant bootstrapped p-value at 0.21, but even this is far off the 5% level of significance. Otherwise the p-values presents somewhat same-level-values as Panel A. The top performer has an increase in the p-value from 0.54 to 0.81, and the second-best performer increases its p-value from 0.11 to 0.55. There are only minor differences in the top five and ten percentile, displaying no change in the top five percent and a slight decrease from 0.81 to 0.76 in the top ten percent. These changes are insignificant to the conclusion drawn from Panel A, providing no evidence to challenge the null hypothesis based on these values. Among the worst-performing funds, we observe bootstrapped p-values that are mostly significant except the worst performing fund with a p-value of 0.17, providing a t-statistic of alpha of -3.22. The percentile that reports the lowest p-value is the bottom 5%. It reports a t-statistic of alpha of -2.45 with a p-value of 0.00, which is equal to Panel A. The bottom 10% displays the same p-value as Panel A with 0.01 leaving it to remain significant. The second-worst performer have slight increase in p-value from 0.01 to 0.02, opposed to the third-worst performer's significant result of 0.00, down from 0.02. The performance in Panel B is coherent to the patterns in the Panel A and affirming the conclusion of rejecting the null for the bottom performers.

Our conclusions on mutual fund managers skills would change if basing the analysis on a parametric approach rather than the bootstrap. The parametric p-values are significantly different from those in the bootstrap among the top performers and underline the importance of the bootstrap, as illustrated by Kosowski et al. (2006). In Panel A, we observed that the parametric p-values are significant for almost all reported columns except for the third-best performer, while the bootstrapped p-values are not significant at any point or percentile. In Panel B, all p-values in the parametric test are significant except the top 10%, compared to only the bottom performers (except the bottom performer) in the bootstrap. The funds' cross-sectional bootstrapped p-values are more distinguished than their parametric p-values in both the left- and right tail. The probability mass in the left tail of the cross-section is increased in the bootstrap resulting in fatter tails and would, in this case, lead to a rejecting of the null as abnormal performance would be evident in all points.

Using the unconditional Carhart (1997) four-factor model, Figure 5 elaborates further displaying alpha t-statistic distributions. The figure is divided into six panels showing different percentile points, including the top and bottom performing funds. The dashed line in all panels are the actual (estimated) t-statistic of alpha. Panels A1-A3 depicts the right tail of the distribution, whereas B1-B3 reports the left tail. Panel A1 is left-skewed, including alpha t-statistics, from around one to about 6 in rare cases. Panel A1 report a t-statistic of 2.23, where the bootstrap generated too many alpha-statistics above this alpha. This is an indication that the alpha t-statistic generated in the top fund is due to luck rather than stock-picking skill, resulting in a lack of evidence at a 5% significance level failing to reject the null. Based on the results of the parametric t-test, there are no indications to reject the null hypothesis, which is coherent to the bootstrap results reported in Table 5. Panels A2 and A3 report alpha t-statistic of 1.94 and 1.19; both have insignificant p-values at 0.21 and 0.76, failing to reject the null, despite the parametric t-test producing significant p-values in contrast with the bootstrap (Table 5). Both panels are left-skewed, producing alpha t-statistic in the range of 0.5 to 3, and the results would support luck-based performance rather than stock-picking skill. In the right tail cases, the parametric standard t-tests are indicating misleading inference in all reported cases, also illustrating the statistical power of the bootstrap procedure.

Panel B1-B3 illustrates the situation in the bottom tier of the sample, where Panel B1 produced alpha t-statistic of -3.22 and a p-value of 0.17, failing to reject the null. Panel B2 and B3, reporting bottom 5% and 10%, have significantly lower p-values at 0.00 and 0.01, producing alpha t-statistic of -2.45 and -1.73, respectively. Despite the parametric t-statistic indicating significance at a 5% level in the bottom five and ten percentile, the bootstrap upholds the null hypothesis rejection. When considering the statistical significance in the tails of the performance distribution, these results are underlining the importance of a bootstrap due to its complex distribution properties. Our bootstrap results provide of rejecting the null in the left tail only, which means that no superior fund manager can generate positive alphas net of cost based on skill. The left tail provides a different result, as our tests produce significant results providing evidence of poor stock-picking skills. This supports Kosowski et al. (2006) and Fama and French (2010), who identified evidence of lack of skill among the lowest-performing funds. Kosowski et al. (2006) also found evidence of skill among top performers, as opposed to our findings, not finding evidence of skill.

**Figure 5: Bootstrapped versus Estimated T-statistic of Alpha.**

The panels display various percentiles in the cross-section plotting the kernel density estimates of alpha distribution using bootstrapped unconditional four-factor t-statistic. This is illustrated with the solid line in the plots, while the vertical plotted line displays the estimated fund t-statistic. The kernel density estimate is shown along the y-axis and the t-statistic of alpha on the x-axis. Panels A1-A3 reports the right tail of the performance distribution including the top fund, top five and top ten percent. Panels B1-B3 reports the left tail of the performance distribution, including the bottom fund, bottom five, and bottom ten percent. The statistics are based on 10,000 bootstrap resamples and are ranked on their t-statistic of alpha in both panels.

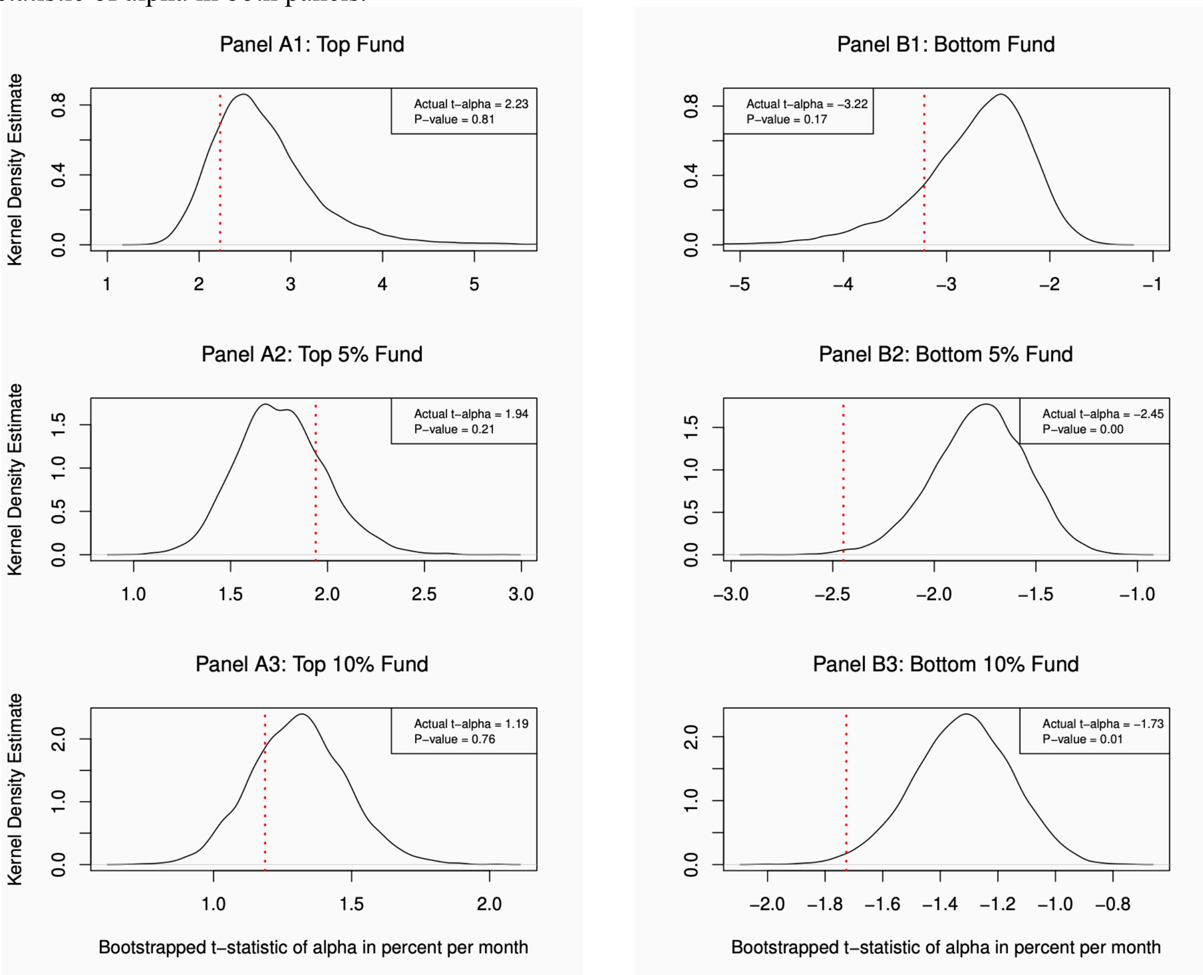


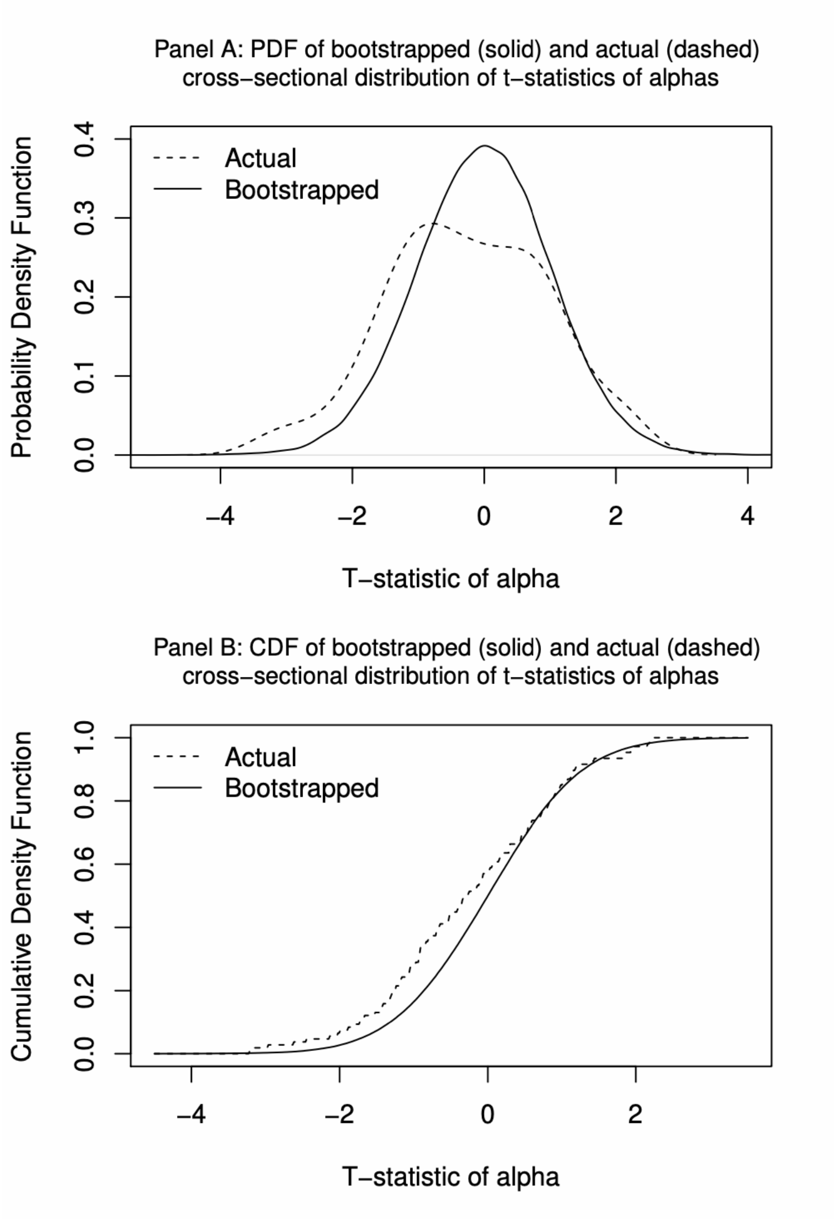

Figure 6 consists of Panels A and B using the probability density function (PDF) in Panel A and cumulative density function (CDF) in Panel B. Panel A compares the bootstrapped generated cross-sectional distribution alphas sorted by the estimated fund t-statistic of alpha. The shapes of the two densities are significantly different. The bootstrapped distribution has far more probability mass in the center of the distribution, while the actual t-statistic has more mass in the right and especially the left tails. The actual t-statistic distribution displays complicated aspects, one being "shoulders." The shoulders can be observed, e.g., around -2 and especially at 0, t-statistic of alpha. The bootstrap offers more competent measures on fat versus thin tails of the actual distribution. Also, it possesses the ability to apprehend complex shapes of the full cross-sectional distribution of t-statistic. This results in the inference based on the normality assumption being different from the bootstrap inference, illustrating that our sample has a non-normal cross-sectional distribution of the funds' actual t-statistic.

The results in Panel B, plotting the cumulative probability function, can substantiate the observations made in Panel A. In Panel A, there is far more probability mass in the left tail of the actual distribution than the bootstrap. The actual distribution lies significantly above the bootstrapped t-statistic of alpha of -3.2 to 0.2. On accusation, the right tail of the actual distribution dips below the bootstrap and are more similar to the bootstrap distribution. Looking at the distribution for both actual and bootstrapped t-statistic of alpha, the actual alphas significantly lower in the middle of the distribution, indication an underperformance opposed to what to expect in the bootstrap. In line with prior results, the test results provide evidence of the poorest performers lacking skill rather than being unlucky. All tests considered, the results produced p-values that are close to being significant and parametric p-values are significant at a 5% level and lower. These results compared to Panel B (Figure 6) support the rejecting of the null hypotheses among the poorest performers supporting previous findings.

Based on parametric inference, the result suggests that superior performance is luck-based while the inferior performance is caused by a lack of skill. The bootstrap evidence supports this, as the alpha distribution and the t-statistic of alphas display complicated and non-normal properties, illustrating the bootstrap's statistical power. The results provide evidence to reject the null for the poorest but not for the top performers, meaning that there is abnormal performance generated by a lack of skill among the worst Norwegian mutual fund managers.

**Figure 6: Cross-section of Alpha T-statistic – Bootstrap versus Estimated**

The figure is divided into two panels illustrating using the probability density function and the cumulative density function. Panel A displays the bootstrapped cross-sectional distribution of the t-statistic of mutual fund alphas (solid line) and the kernel (probability) density estimated of actual alphas (dashed line). Panel B shows the kernel density estimates based on a cumulative density function of the distributions. The panels are for the full period 1987-2019, and the four-factor model is applied to all mutual funds in the sample to compute the t-statistic of alphas.



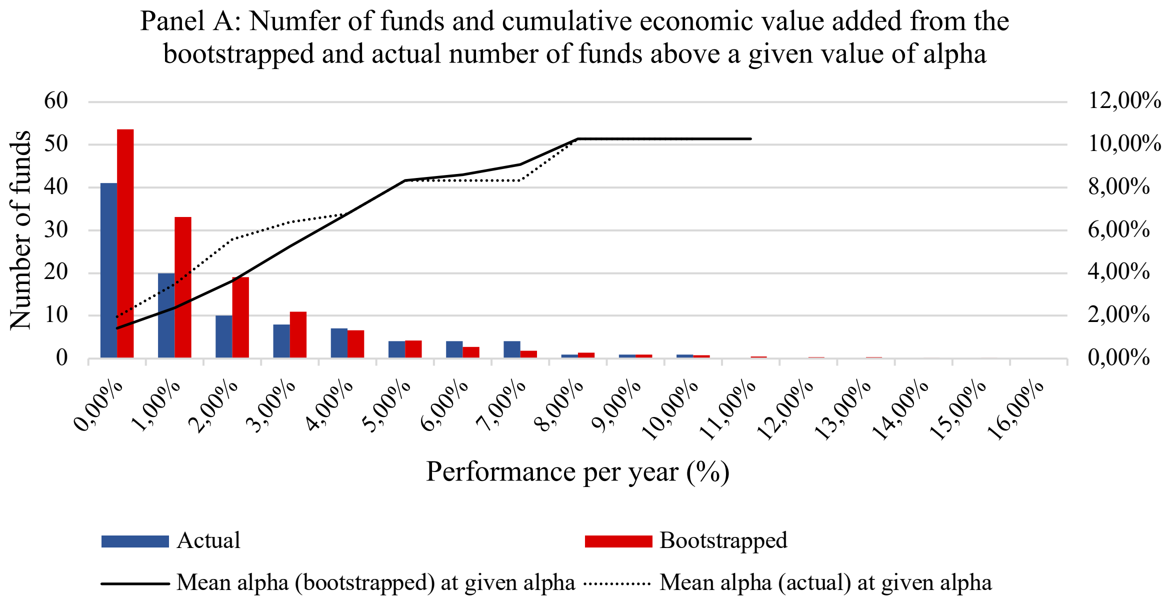
### 5.2.2 Economic Impact

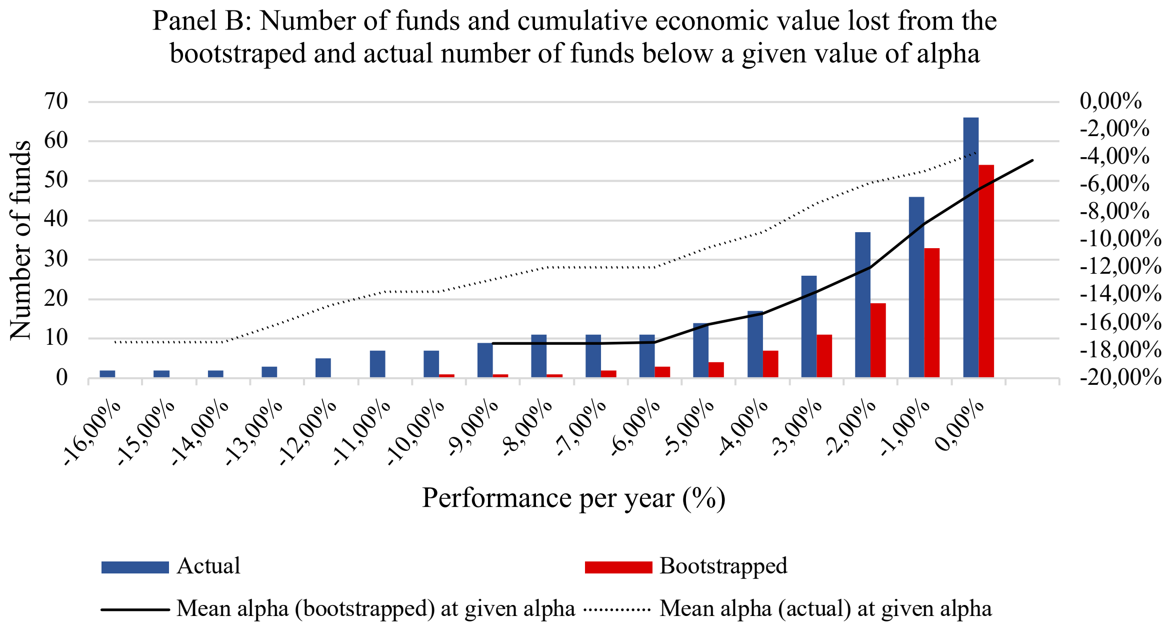
Panel B in Figure 6 plots the cumulative density function indicating how the actual CDF is positioned, more precisely if it is positioned below the bootstrapped CDF in a specific region. The bootstrapped distribution has another use as to calculate how many funds by chance would exceed a given level of performance among our sample funds. This would account for all funds in the sample with a life span longer than twelve months, and the number generated can be used to be compared to the number of funds (actual estimated alpha) exceeding this performance level.

Figure 7 shows the cumulative number of funds from the bootstrap, and the original distribution, plotted in two different panels. Panel A reports funds that outperform a given positive alpha by average across all bootstrap iterations. In contrast, in Panel B, report the funds underperforming a given negative alpha. The left y-axis displays the number of funds within each alpha percentile while the right y-axis reports the mean alpha within these percentiles. For example, in Panel A, four funds indicate an alpha estimate outperforming the 5% set level per year by chance. In reality, four funds can reach such an alpha. The discrepancies increase closer to zero alpha; at a 2% alpha, 19 funds indicate outperforming this alpha level by chance every year, compared to only ten funds in reality. Continuing to Panel B, there are indications that 14 funds were generating alpha estimates below -5%. This is higher than the anticipated number of four funds generated by random. These tests provide evidence that the mutual fund managers generate both positive and negative alphas and alpha t-statistics in the extreme funds. Studying Panel A in Figure 7, specifically the subgroup 4%, around seven funds indicates having sufficient stock-picking talent to exceed their cost. As the actual number is seven as well, this indicates that all stock-pickers outperforming a set alpha of 4% are relying on skill rather than luck. Moving further down the right tail, looking at fund managers generating an alpha greater than 7%, the percentage of fund managers having adequate talent in stock-picking to exceed their cost drops down to 50%

**Figure 7: Cumulative Value Added (lost) in Percent**

The figure reports cumulative value added in percent above or under set points of alpha given by actual and bootstrapped cross-sectional distributions of given funds. The number of funds performing at the given level of alpha is shown as vertical bars given at the leftmost y-axis, while the value added (lost) is given by the leftmost y-axis. Panel A reports on positive alphas and Panel B for negative alphas. The dashed line represents the mean alphas for the actual number of funds within the given percentile, and the solid line reports the mean alphas for the bootstrapped estimated number of funds.



## 5.3 Sensitivity Analysis

In this thesis, we have relied on the method of Kosowski et al. (2006) to estimate cross-sectional and individual distributions of alpha. As there are more bootstrap procedures, we want to determine whether our bootstrap results change when altering the approach. Changing the procedure will, in some cases, affect specific assumptions and change the null hypothesis. In each section, these changes are addressed and concluded as to the impact it has on our results.

### 5.3.1 Time-Series Dependence - I

Following the studies done by Politis and Romano (1994), they argued for allowing dependence in return residuals by adopting the stationary bootstrap method. On the other hand, our baseline bootstrap results are relying on the assumption of residuals being both independent and equally distributed. The method of Politis and Romano (1994) keeps the dependence in the return residuals by different length block-resampling. Our null hypothesis of no abnormal performance (zero true performance) in individual funds remains despite the change in the residual dependence assumption.

The essential thing to determine when performing analysis using a stationary bootstrap method is the optimal block length. Hall, Horowitz, and Jing (1995) argue that the block length is determined by the following asymptotic formula: $l \sim T^{\frac{1}{h}}$ ($T$ = number of observations; $h$ = 3, 4, or 5). They found that $h$ is context-dependent. For one-sided distribution functions of the given test statistic, the block bootstrap estimator is given as $h$=4. In our situation, this generated a block length of 4. For two-sided distributions, $h$=5 and $h$=3 when determining block bootstrap estimators of variance.

We allow for dependence in return residuals in our robustness check by implementing the stationary bootstrap by Politis and Romano (1994). This approach resamples data blocks of random length and draws a string of independent and identically distributed random variables from a geometric distribution. This arranges the blocks to output a stationary pseudo-time series. We compare the bootstrap results under one monthly return block lengths, a block length of 4, and random block lengths of 2 and 10 monthly returns.

The stationary bootstrap test as described, and we provide the results in Appendix E.I. Looking at these results, when testing different block lengths, we experienced a minimal difference in our findings. According to this test, we can conclude that our results are robust.

### 5.3.2 Residual and Factor Resampling - II

The next test examined whether our results change using randomized factor returns by interrupting autocorrelation in the factor returns. This procedure is executed by resampling regression residuals and factor returns. We use the same draw across all funds when resampling factor returns. By doing so, the correlation between factor returns and all funds is preserved generating individual bootstrap (*b*) and for each fund (*i*) in the following formula (Kosowski et al., 2006):

$$MKT_t^b, SMB_t^b, HML_t^b, PR1YR_t^b, t_F = \tau_{T_{i0}}^b, \dots, \tau_{T_{i1}}^b \tag{10}$$

$$\hat{\varepsilon}_{i,t}^b, t_e = s_{T_{i0}}^b, \dots s_{T_{1l}}^b \tag{11}$$

From this, we construct a time-series of monthly returns for the fund (*i*) for each bootstrap iteration (b), while still enforcing our null hypothesis of no abnormal return (zero alpha).

$$\tilde{r}_{i,t}^b = \beta_{1i} MKT_{t_F}^b + \beta_{2i} SMB_{t_F}^b + \beta_{3i} HML_{t_F}^b + \beta_{4i} PR1YR_{t_F}^b + \tilde{\varepsilon}_{i,t_\varepsilon}^b \tag{12}$$

Using this equation (12), we calculated each fund using the Carhart (1997) four-factor model to estimate each fund's alpha and t-statistic. The results are reported in Appendix E.II, and we can conclude that our findings are insignificantly different from our baseline bootstrap. Hence, we can conclude the results are robust.

### 5.3.3 Cross-sectional Bootstrap - III

So far, in our bootstrap procedure, we have assumed a cross-correlation of zero. However, as an extension to our baseline bootstrap, we ran a cross-sectional bootstrap where the residuals are bootstrapped, but the cross-sectional correlations between residuals of all funds are kept. It is reasonable to expect a certain level of correlation as the Norwegian mutual funds in our sample must comprise a minimum of 80% Norwegian stocks. Fund residual cross-correlation may occur when funds buy or hold a set of specific stocks over a specified period. This correlation could significantly impact the tails of our alpha distribution and may cause a residual bias. Dealing with this issue, we have implemented a cross-sectional bootstrap procedure allowing cross-correlation in residuals. The purpose of this is to examine whether this impacts our results in a significant way. The main difference between the two approaches is that we draw $T$ periods from {t=1,…,$T$} making a re-indexed time sequence of all funds ($\tilde{T}_b$ ) before resampling residuals, making sure that we preserve all, if any, cross-sectional correlation in the residuals

Using this approach, however, may generate entries that do not exist in our original sample. To eliminate this problem, we have set a limitation of 24 observations instead of 12 in the baseline bootstrap procedure. Meaning, we will remove any fund with less than 24 observations from this specific test. For a more extensive look at the results of the cross-sectional bootstrap, see Appendix E.III. Based on the cross-sectional bootstrap procedure, there are no changes in the t-statistic of alpha in either the left- or right tail. Examining the parametric p-value of each quintile, we observe some minuscule changes leaving no funds in the right tail significant at a 95% level. For the left tail, the bottom 10% worst performing fund becomes insignificant at the 95% level. More interesting are the bootstrapped p-values. Studying the cross-sectional bootstrapped p-values of the top-performing funds reports a decrease in all the top quintiles listed. E.g., the top-performing fund has a bootstrapped p-value of 0.48, down from 0.81 in the baseline bootstrap. Neither of the cross-sectional bootstrapped p-values are significant at a 95% level, meaning that the results of this test do not oppose previous conclusion for the top-performing funds. Regarding the bottom performing funds, they do not report bootstrapped p-values due to missing values of t-statistic of alpha in each bootstrap round meaning we cannot draw a conclusion in the bottom tier. The results in this robustness test do not provide evidence to contest previous findings.

### 5.3.4 Portfolios of Funds - IV

From the argumentation of Kosowski et al. (2006), it is necessary to consider the corresponding average statistics in each tail for portfolios of funds to determine whether individual cross-sectional fund alpha analysis is affecting our inference. The cross-sectional bootstrap procedure described in the previous section remains here for a minimum of 12 observations, and the test functions as a robustness check for our results. In this section, we have changed the null hypothesis to account for portfolios instead of individual funds. The null hypothesis for this test states no abnormal returns (zero true performance) in portfolios.

The funds are individually ranked on their t-statistic of alpha before being bundled into portfolios of 2, 3, and 5 funds. For example, looking at portfolios of 2 funds, we estimated the four-factor model (Carhart, 1997) and ranked each fund individually by their t-statistic of alpha. The top-performing portfolio consists of the two highest-performing funds, and the second-best portfolio contains the third and fourth, and so on. We ran the test using three different portfolio set-ups, the first being portfolios of 2, then 3 and 5. We calculated the alpha of each portfolio (t-statistic) with adjacent parametric and bootstrapped p-values. The p-value states the probability of observing the average alpha (t-statistic), which is observed under the assumption of zero alpha (t-statistic).

The results of our test are reported in Table 6, and more detailed description are provided in Appendix E.IV. Our baseline bootstrap has significant bootstrapped p-values for the bottom 10th-3rd funds, as reported before. Both portfolios of 2 and 5 funds reported in Panel B and C in Table 6 shows a significant change from the baseline bootstrap. In these panels, the bottom performing portfolios do not have bootstrapped p-values due to missing values of t-statistic of alpha in each bootstrap iteration. The top-performing funds are not significant as in the baseline bootstrap, but the bootstrapped p-values are significantly lower. Looking at Panel C in Table 6, the top-performing portfolio of 5 funds reported significant bootstrapped p-value of 0.04. This indicate that when the top-performing portfolio managers' skills are combined, the alpha t-statistic observed is not only due to luck. The tendency of generating NA-values in the left tail of the distribution continues from Panel B. Hence, we cannot compare to the baseline bootstrap. These results are somewhat differentiated from previous findings indicating skill among top performers when teamed up. These indications are not robust enough to challenge our previous conclusions but illustrate the challenges in interpreting results in financial analysis.

**Table 6: Portfolios of Funds**

The table provides the average statistic corresponding to portfolios in both left- and right tail distribution of alpha for the full period 1987-2019. Panel A reports the baseline bootstrap in a different set-up than previously displayed, now reporting the top and bottom ten funds in our sample. The funds are ranked according to their t-statistic of alpha and bundled into portfolios, each consisting of two and five, respectively. Panel B reports portfolios of 2 funds (53 portfolios) where the top and bottom ten are displayed. Panel C reports portfolios of 5 funds (53 portfolios). The columns are the adjacent portfolios for each panel. For each panel, row 1 reports the estimated t-statistic of alpha. Panel 2 displays the cross-sectionally annualized associated alpha for the t-statistic, whereas row 3 displays the parametric p-values of the t-statistic. The statistics are based on 10.000 bootstrap resamples and are ranked on their t-statistic of alpha in all panels.

| | Bottom | 2nd | 3rd | 4th | 5th | 6th | 7th | 8th | 9th | Bottom 10th | Top 10th | 9th | 8th | 7th | 6th | 5th | 4th | 3rd | 2nd | Top |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **Panel A: Baseline bootstrap** | | | | | | | | | | | | | | | | | | | | |
| T-alpha | -3.22 | -3.18 | -2.96 | -2.63 | -2.45 | -2.14 | -2.03 | -1.99 | -1.89 | -1.81 | 1.24 | 1.36 | 1.43 | 1.82 | 1.83 | 1.94 | 1.94 | 2.15 | 2.19 | 2.23 |
| Bootstrapped p-value | 0.17 | 0.02 | 0.00 | 0.01 | 0.00 | 0.02 | 0.02 | 0.01 | 0.01 | 0.01 | 0.76 | 0.65 | 0.62 | 0.11 | 0.20 | 0.21 | 0.38 | 0.33 | 0.55 | 0.81 |
| Parametric p-value | 0.00 | 0.00 | 0.00 | 0.00 | 0.01 | 0.02 | 0.02 | 0.02 | 0.03 | 0.04 | 0.11 | 0.09 | 0.08 | 0.03 | 0.03 | 0.03 | 0.03 | 0.02 | 0.01 | 0.01 |

| | Bottom | 2nd | 3rd | 4th | Bottom 5th | Top 5th | 4th | 3rd | 2nd | Top |
|---|---|---|---|---|---|---|---|---|---|---|
| **Panel B: Portfolios of 2 funds, 53 total portfolios** | | | | | | | | | | |
| T-alpha | -3.72 | -3.19 | -2.18 | -2.13 | -1.95 | 1.45 | 1.80 | 2.00 | 2.40 | 2.43 |
| Bootstrapped p-value | NA | NA | NA | NA | NA | 0.26 | 0.14 | 0.13 | 0.09 | 0.24 |
| Parametric p-value | 0.00 | 0.00 | 0.01 | 2.00 | 0.03 | 0.07 | 0.04 | 0.02 | 0.01 | 0.01 |

| | Bottom | 2nd | 2nd | Top |
|---|---|---|---|---|
| **Panel C: Portfolios of 5 funds, 21 total portfolios** | | | | |
| T-alpha | -3.37 | -2.14 | 2.15 | 2.99 |
| Bootstrapped p-value | NA | NA | 0.08 | 0.04 |
| Parametric p-value | 0.00 | 0.02 | 0.02 | 0.00 |

### 5.3.5 Length of Data Records - V

As the final robustness check, we examined whether the length of our data impacts our results by imposing minimal observations. When applying this method, we tested whether our results are sensitive to these changes. Kosowski et al. (2006) identifies that short-lived funds tend to have a higher variation and volatility in their alpha estimates than long-lived funds. Trying to eliminate this factor, we have set a set of required amounts of observations, to try and remedy this fact. We are using the t-test in this case, since it is less sensitive to outliers (Kosowski et al., 2006). When applying this to our sample, we have generated new bootstraps with a minimum amount of observations of 24, 36, and 60. The results report minimal differences from the baseline bootstrap and are reported in Appendix E.V. We note a similar pattern from the previous results where almost all bottom performers are statistically significant, except for the worst performer.

## 5.4 Sub-periodical Bootstrap Test

In previous sections, we ran the cross-sectional bootstrap for the entire period 1987-2019. For this section, we study the changes in bootstrap results for different subperiods, each period with a minimum of twelve observations. The periods each consist of the eleven-year periods 1987-1997; 1998-2008 and 2009-2019. The results are reported in Table 7, divided into four panels, Panel A for the full period and Panel B-D for each period, respectively. Table 7 reports for the top and bottom ten funds instead of different percentiles and the top- and bottom three funds in Table 5, due to fewer funds in each period than for the full period.

Starting with the first period reported in Panel B, reporting 38 funds in 1987-1997, and the bottom performers, the period displays different qualities compared to the full period. The bottom funds have changed compared to the baseline; however, the bottom fund remains statistically insignificant at a 95% level. The second-worst performer has become insignificant in addition to the fourth-worst fund compared to the full period (Panel A). The results remain insignificant for the top performers, and the bootstrapped p-values have overall increased significantly. The second-best performer in the full period is notably the top-performer in Panel B, with a decrease in bootstrapped p-value, indicating a somewhat higher skill level in this period, but not generating a significant value.

For the second period, Panel C (1998-2008), the same trend continues reporting a reduction in all bottom performers leaving all values significant when testing at a 95% level of certainty. The top performers also show the same symptoms of non-significant values and an even more significant increase compared to Panel B. Notably; all bootstrapped p-values are close to or equal to 1, which is quite different from all other periods, including the full period. Panel D reports for the last period 2009-2019, where we notice a drastic change in results in the bootstrapped p-values for the bottom performers compared to the other panels. In this period, all top performers' values are non-significant, and all top performers have reduced bootstrapped p-values compared to all other periods (but remain non-significant). Most notably for the top performers are the 6th best performing fund having a bootstrapped p-value of 0.07.

These test results provide additional evidence to reject the null hypothesis for no true performance at a 95%-level of certainty for bottom performers in the first (1987-1997) and second (1998-2008) period, except for the bottom performer in the first period. As our baseline bootstrap reports that nine of the ten bottom performers have significant bootstrapped p-values, these results suggest that the bottom performers in the first and second periods result from poor skill rather than bad luck. For the third period, the results are reporting contradicting results influencing the full-period baseline bootstrap. As a result, we reject the null for the bottom performers in the first (1987-1997; except bottom performer) and second (1998-2008) period, but fail to reject for the third period (2009-2019).

**Table 7: Baseline Bootstrap for Sub-periods**

The table provides cross-sectional bootstrapped four-factor alphas results of all Norwegian Mutual funds in our sample for the different sub-periods, each containing eleven years. All panels report on various percentiles and quintiles where Panel A reports for the full period 1987-2019, Panel B for 1987-1997, Panel C for 1998-2008, and Panel D for 2009-2019. The first row reports the t-statistic of alpha, while the second row reports the adjacent cross-sectional bootstrapped p-value, and the third row reports the parametric p-value of the t-statistics. The statistics are based on 10,000 bootstrap resamples and are ranked on their t-statistic of alpha in both panels.

| | Bot. | 2nd | 3rd | 4th | 5th | 6th | 7th | 8th | 9th | Bot. 10th | Top 10th | 9th | 8th | 7th | 6th | 5th | 4th | 3rd | 2nd | Top |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **Panel A: Fund Ranked on t-statistic Four-Factor Model Alphas full period (Baseline; 1987-2019)** | | | | | | | | | | | | | | | | | | | | |
| T-alpha | -3.22 | -3.18 | -2.96 | -2.63 | -2.45 | -2.14 | -2.03 | -1.99 | -1.89 | -1.81 | 1.24 | 1.36 | 1.43 | 1.82 | 1.83 | 1.94 | 1.94 | 2.15 | 2.19 | 2.23 |
| Bootstrapped p-value | 0.17 | 0.02 | 0.00 | 0.01 | 0.00 | 0.02 | 0.02 | 0.01 | 0.01 | 0.01 | 0.76 | 0.65 | 0.62 | 0.11 | 0.20 | 0.21 | 0.38 | 0.33 | 0.55 | 0.81 |
| Parametric p-value | 0.00 | 0.00 | 0.00 | 0.00 | 0.01 | 0.02 | 0.02 | 0.02 | 0.03 | 0.04 | 0.11 | 0.09 | 0.08 | 0.03 | 0.03 | 0.03 | 0.03 | 0.02 | 0.01 | 0.01 |
| **Panel B: Fund Ranked on t-Statistic Four-Factor Model Alphas (1987-1997)** | | | | | | | | | | | | | | | | | | | | |
| T-alpha | -2.98 | -2.67 | -2.65 | -1.89 | -1.85 | -1.74 | -1.68 | -1.31 | -1.12 | -1.10 | 0.66 | 0.78 | 0.91 | 1.02 | 1.19 | 1.19 | 1.24 | 1.38 | 1.41 | 2.19 |
| Bootstrapped p-value | 0.26 | 0.07 | 0.01 | 0.08 | 0.03 | 0.02 | 0.01 | 0.05 | 0.09 | 0.05 | 0.51 | 0.44 | 0.39 | 0.38 | 0.30 | 0.47 | 0.61 | 0.64 | 0.83 | 0.49 |
| Parametric p-value | 0.00 | 0.00 | 0.00 | 0.03 | 0.03 | 0.04 | 0.05 | 0.09 | 0.13 | 0.14 | 0.26 | 0.22 | 0.18 | 0.16 | 0.12 | 0.12 | 0.11 | 0.08 | 0.08 | 0.01 |
| **Panel C: Fund Ranked on t-Statistic Four-Factor Model Alphas (1998-2008)** | | | | | | | | | | | | | | | | | | | | |
| T-alpha | -3.66 | -3.63 | -3.19 | -3.17 | -3.12 | -2.90 | -2.57 | -2.34 | -2.27 | -2.18 | 0.73 | 0.75 | 0.92 | 1.01 | 1.07 | 1.13 | 1.13 | 1.22 | 1.24 | 1,55 |
| Bootstrapped p-value | 0.04 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 1.00 | 1.00 | 0.99 | 0.98 | 0.99 | 0.99 | 1.00 | 1.00 | 1.00 | 1,00 |
| Parametric p-value | 0.00 | 0.00 | 0.00 | 0,00 | 0.00 | 0.00 | 0.01 | 0.01 | 0.01 | 0.01 | 0.23 | 0.23 | 0.18 | 0.16 | 0.14 | 0.13 | 0.13 | 0.11 | 0.11 | 0,06 |
| **Panel D: Fund Ranked on t-Statistic Four-Factor Model Alphas (2009-2019)** | | | | | | | | | | | | | | | | | | | | |
| T-alpha | -1.87 | -1.42 | -1.37 | -1.33 | -1.30 | -1.05 | -1.05 | -0.98 | -0.91 | -0.84 | 1.13 | 1.17 | 1.24 | 1.43 | 1.82 | 1.84 | 1.95 | 2.15 | 2.15 | 2.19 |
| Bootstrapped p-value | 0.93 | 0.99 | 0.97 | 0.94 | 0.89 | 0.98 | 0.95 | 0.95 | 0.95 | 0.96 | 0.57 | 0.60 | 0.62 | 0.41 | 0.07 | 0.14 | 0.17 | 0.17 | 0.42 | 0.73 |
| Parametric p-value | 0.03 | 0.08 | 0.09 | 0.09 | 0.10 | 0.15 | 0.15 | 0.16 | 0.18 | 0.20 | 0.13 | 0.12 | 0.11 | 0.08 | 0.03 | 0.03 | 0.03 | 0.02 | 0.02 | 0.01 |

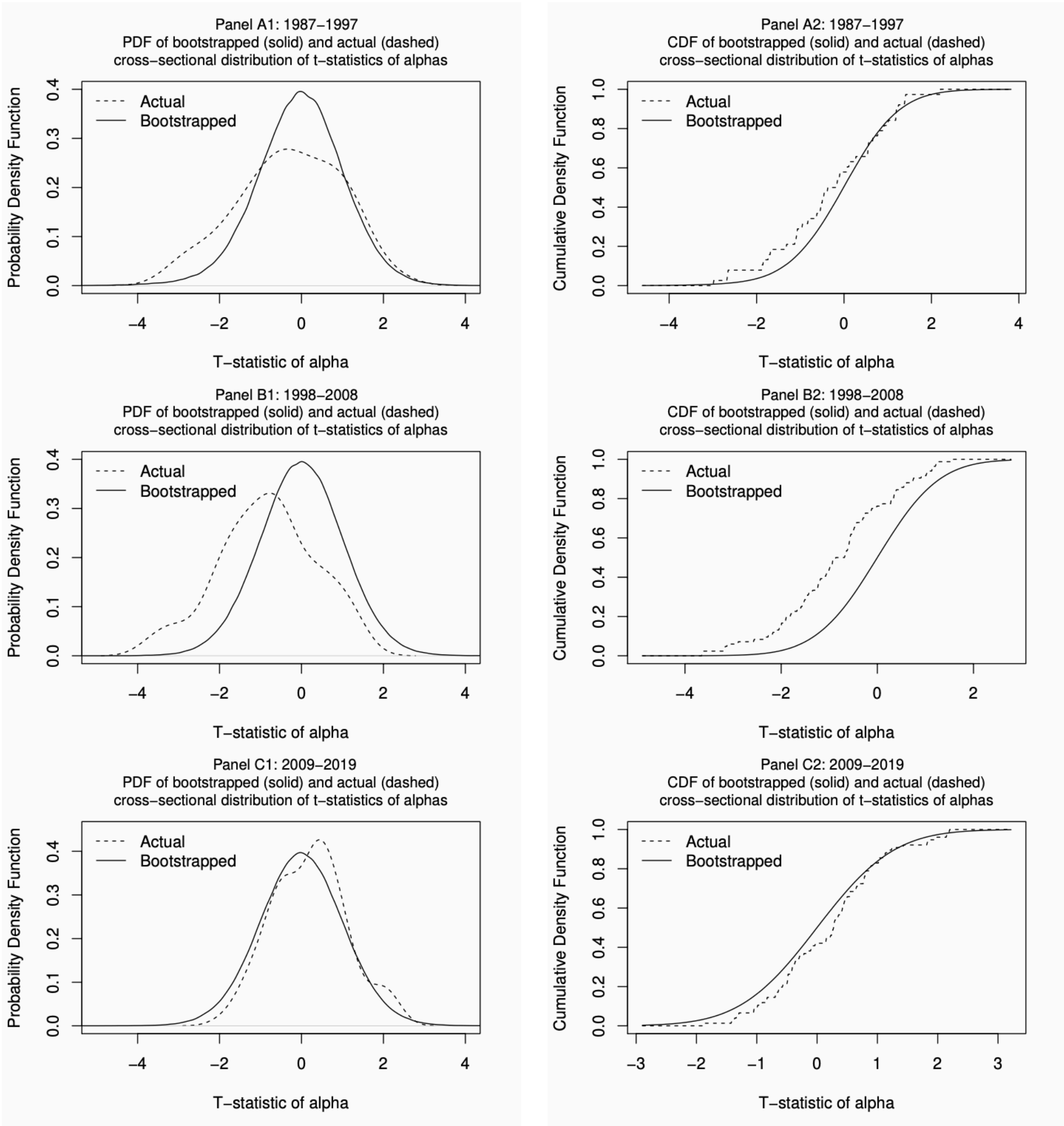
To further analyze the results, we compare the bootstrapped distribution of alphas to the cross-sectional distribution in Figure 8 below for the same three sub-periods, as mentioned before (1987-1997; 1998-2008; 2009-2019). Panel A1 and A2 reports the probability (kernel) density function (PDF) and the cumulative density function (CDF) for the first period. Looking at the PDF in Panel A1 the actual cross-sectional distribution has more mass in the left tail and less mass in the center than the bootstrapped results. In the right tail, the results are almost overlapping. The CDF-function in Panel A2, the bootstrapped estimation of alphas, are lower than the actual distribution in both the right- and the left tail, but less so in the right tail. When studying the visual presentation, it is a slight difference between the actual and bootstrapped distribution of alphas in the PDF but less in the CDF. The second period is reported in Panels B1 and B2, wherein B1 the PDF clearly shows a heavy mass in the left tail of the distribution of actual alphas, and less mass in the right tail than the bootstrapped distribution. Panel B2 also displays heavy mass in the left tail for the actual distribution of alphas and more mass in the right tail. At the very end of the right tail distribution, it evens out with the bootstrapped results.

There are significant differences between the actual and bootstrapped cross-sectional distribution of alpha. Panel C1 and C2 reports for the last period, and starting with Panel C1 reporting the PDF for 2009-2019, the distribution of mass has shifted from left in Panel B1 to the right tail. In the left tail, the actual distribution overlaps with the bootstrapped results while the center displays more mass in the right tail, before leveling out with the bootstrapped distribution as it continues to the right. The CDF in Panel C2 has a shift in the distribution for the previous period lying below the bootstrapped results in the left tail and overlapping in the right tail. The second period's visual presentation displays minuscule differences between the cross-sectional of bootstrapped and actual distribution of alpha t-statistic.

As a result, starting with the last period 2009-2019, there is no evidence of rejecting the null hypothesis in the left tail of the distribution opposed to the two first periods; 1987-1997 and 1998-2008. There is no evidence to reject the null in the right tail in any period. This is in keeping with Table 7 substantiating the evidence of lack of skill in the bottom performers. The last period's findings are continuing the trend of no true performance at either end of the distribution, failing to reject the null.

**Figure 8: Cross-section of Alpha T-statistic for Sub-periods**

The figure is divided into six panels illustrating using the probability density function and the cumulative density function. Panel A1 and A2 report the period 1987-1997, Panel B1 and B2 report 1998-2008, and Panel C1 and C2 for the last period 2009-2019. Panels A1, B1, and C1 displays the bootstrapped cross-sectional distribution of the t-statistic of mutual fund alphas (solid line) and the kernel (probability) density estimated of actual alphas (dashed line). Panels A2, B2, and C2 show the kernel density estimates based on the distributions' cumulative density function. The four-factor model is applied to all mutual funds in the sample to compute the t-statistic of alphas.



# 6 Conclusion

This thesis investigates whether there is significant evidence of skilled managers in 107 Norwegian mutual funds between 1987-2019. We are using a dataset from the TITLON database, reporting funds' monthly net returns free of survivorship bias. Our thesis's primary performance model on both the aggregate and individual levels is the Carhart (1997) four-factor model. We apply a bootstrap approach similar to Kosowski et al. (2006), to distinguish between lucky and skilled managers. The bootstrap is also implemented to evaluate our results' statistical significance, intricate dependencies in the cross-section, and the non-normal returns.

We conclude that actively managed Norwegian mutual funds on aggregate produce a non-significant alpha that is more or less equal to zero (0.04%), net of cost. This suggests that if managers do inhabit stock-picking skills, they collect their abnormal performance as fees, leaving nothing for the investor.

Evaluating funds on the individual level, we find no significant evidence of superior managers; we fail to reject our null hypothesis of no true performance in our right tail. However, we find trustworthy evidence of the lack of skill in our worst-performing managers. They are not merely unlucky; they are unskilled. Thus, rejecting the null hypothesis for our distribution's left tail. We emphasize the importance of the bootstrap, since the results vary significantly between bootstrap and parametric tests. Additionally, following the sensitivity analysis of Kosowski et al. (2006), our results are robust, following our sensitivity analysis.

Empirical results in this thesis are similar to previous research done in mutual fund performance. They are stating the difficulty of generating a positive abnormal return and supporting the EMH. We cannot justify investing in an active Norwegian mutual fund; investors should instead invest in a passive, low-cost index fund. Knowing that if the manager can create a positive abnormal return, it will be collected as service fees.

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## Appendix A

**Table A.I: Mutual Fund Descriptive Statistics (1/2)**

The tables A.I and A.II contain various descriptive statistics of the 107 Norwegian mutual funds in our sample derived from individual regressions on each fund. Column one reports the monthly observations per fund, and column three reports monthly excess return net of cost—columns 4-8 report standard deviation, kurtosis, skewness, maximum and minimum.

| Name | Obs | Mean | Std. dev. | Kurtosis | Skew | Max | Min |
|---|---|---|---|---|---|---|---|
| ABIF Norge ++ | 56 | 0.007 | 0.068 | -0.556 | -0.302 | 0.135 | -0.163 |
| Alfred Berg Aksjef Norge | 115 | 0.009 | 0.061 | 1.793 | -0.757 | 0.131 | -0.250 |
| Alfred Berg Aksjespar | 106 | 0.008 | 0.066 | 2.077 | -0.853 | 0.133 | -0.280 |
| Alfred Berg Aktiv | 289 | 0.012 | 0.065 | 2.554 | -0.767 | 0.211 | -0.270 |
| Alfred Berg Aktiv II | 182 | 0.008 | 0.073 | 1.179 | -0.596 | 0.179 | -0.274 |
| Alfred Berg Gambak | 350 | 0.013 | 0.065 | 2.662 | -0.397 | 0.285 | -0.274 |
| Alfred Berg Humanfond | 241 | 0.009 | 0.059 | 2.994 | -0.963 | 0.161 | -0.259 |
| Alfred Berg N. Pensjon | 52 | 0.011 | 0.061 | 4.273 | -1.325 | 0.119 | -0.248 |
| Alfred Berg Norge | 147 | 0.009 | 0.071 | 1.832 | -0.953 | 0.171 | -0.270 |
| Alfred Berg Norge +_gml | 197 | 0.009 | 0.068 | 2.182 | -0.965 | 0.171 | -0.269 |
| Alfred Berg Norge Classic | 351 | 0.009 | 0.061 | 3.004 | -1.055 | 0.171 | -0.270 |
| Alfred Berg Norge Etisk | 146 | 0.010 | 0.069 | 2.501 | -1.031 | 0.166 | -0.278 |
| Alfred Berg Norge Inst | 72 | 0.010 | 0.028 | 1.139 | -0.929 | 0.068 | -0.080 |
| Alfred Berg Vekst | 72 | 0.007 | 0.077 | 1.754 | -0.503 | 0.193 | -0.278 |
| Arctic Norwegian Equities Class A | 109 | 0.008 | 0.033 | 1.429 | -0.660 | 0.095 | -0.093 |
| Arctic Norwegian Equities Class B | 110 | 0.008 | 0.035 | 1.358 | -0.560 | 0.098 | -0.092 |
| Arctic Norwegian Equities Class D | 83 | 0.010 | 0.027 | 1.444 | -0.906 | 0.071 | -0.085 |
| Arctic Norwegian Equities Class I | 110 | 0.008 | 0.034 | 1.331 | -0.567 | 0.096 | -0.092 |
| Atlas Norge | 263 | 0.009 | 0.070 | 3.621 | -0.092 | 0.368 | -0.253 |
| Banco Norge | 38 | 0.011 | 0.069 | -0.415 | -0.318 | 0.139 | -0.171 |
| C WorldWide Norge | 294 | 0.011 | 0.059 | 3.024 | -0.886 | 0.198 | -0.275 |
| Carnegie Askje Norge | 210 | 0.012 | 0.067 | 2.012 | -0.853 | 0.198 | -0.275 |
| Danske Invest Aktiv Formuesf. A | 21 | 0.014 | 0.045 | 0.257 | -0.770 | 0.076 | -0.107 |
| Danske Invest Norge Aksj. Inst 1 | 237 | 0.010 | 0.056 | 2.645 | -0.921 | 0.155 | -0.228 |
| Danske Invest Norge Aksj. Inst 2 | 158 | 0.009 | 0.054 | 4.200 | -1.148 | 0.150 | -0.227 |
| Danske Invest Norge I | 312 | 0.009 | 0.058 | 3.583 | -1.027 | 0.149 | -0.288 |
| Danske Invest Norge II | 312 | 0.010 | 0.058 | 3.596 | -1.012 | 0.149 | -0.295 |
| Danske Invest Norge Vekst | 312 | 0.013 | 0.064 | 6.547 | 0.330 | 0.418 | -0.257 |
| Delphi Norge | 307 | 0.013 | 0.068 | 2.033 | -0.541 | 0.230 | -0.249 |
| Delphi Vekst | 193 | 0.009 | 0.075 | 0.984 | -0.331 | 0.255 | -0.230 |
| DNB Norge | 289 | 0.008 | 0.058 | 2.347 | -0.837 | 0.158 | -0.241 |
| DNB Norge (Avanse I) | 327 | 0.009 | 0.063 | 2.071 | -0.954 | 0.160 | -0.264 |
| DNB Norge (Avanse II) | 287 | 0.008 | 0.062 | 2.353 | -0.958 | 0.161 | -0.264 |
| DNB Norge (I) | 295 | 0.010 | 0.071 | 15.154 | 1.301 | 0.593 | -0.242 |
| DNB Norge (III) | 283 | 0.009 | 0.058 | 2.333 | -0.863 | 0.159 | -0.242 |
| DNB Norge (IV) | 206 | 0.012 | 0.056 | 2.896 | -0.879 | 0.160 | -0.242 |
| DNB Norge Selektiv (II) | 214 | 0.010 | 0.058 | 2.324 | -0.765 | 0.169 | -0.237 |
| DNB Norge Selektiv (III) | 307 | 0.010 | 0.058 | 2.190 | -0.814 | 0.170 | -0.241 |
| DnB Real-Vekst | 157 | 0.005 | 0.088 | 24.329 | 2.133 | 0.689 | -0.403 |
| DNB SMB | 226 | 0.012 | 0.069 | 1.138 | -0.466 | 0.175 | -0.265 |
| DNB Norge R | 12 | 0.013 | 0.029 | 0.107 | -1.050 | 0.045 | -0.055 |
| Eika Norge | 196 | 0.012 | 0.056 | 3.891 | -1.011 | 0.184 | -0.249 |
| Eika SMB | 187 | 0.007 | 0.068 | 1.233 | -0.662 | 0.171 | -0.229 |
| FIRST Generator | 112 | 0.011 | 0.056 | 1.331 | -0.757 | 0.155 | -0.189 |
| FIRST Norge Fokus | 14 | 0.010 | 0.029 | 0.187 | -0.890 | 0.052 | -0.061 |
| Fokus Barnespar | 32 | -0.001 | 0.078 | 3.040 | -1.152 | 0.127 | -0.281 |
| Fondsfinans Aktiv II | 48 | -0.001 | 0.067 | -0.195 | -0.223 | 0.143 | -0.165 |
| Fondsfinans Norge | 205 | 0.014 | 0.058 | 2.603 | -0.774 | 0.163 | -0.257 |
| FORTE Norge | 107 | 0.008 | 0.042 | 0.975 | -0.083 | 0.145 | -0.116 |
| FORTE Trønder | 81 | 0.014 | 0.035 | 0.190 | -0.134 | 0.095 | -0.088 |
| GAMBAK Oppkjøp | 19 | 0.003 | 0.055 | 0.123 | 0.319 | 0.139 | -0.092 |
| GJENSIDIGE AksjeSpar | 152 | 0.009 | 0.066 | 2.111 | -0.935 | 0.166 | -0.267 |
| GJENSIDIGE Invest | 104 | 0.013 | 0.059 | 2.288 | -0.834 | 0.133 | -0.212 |

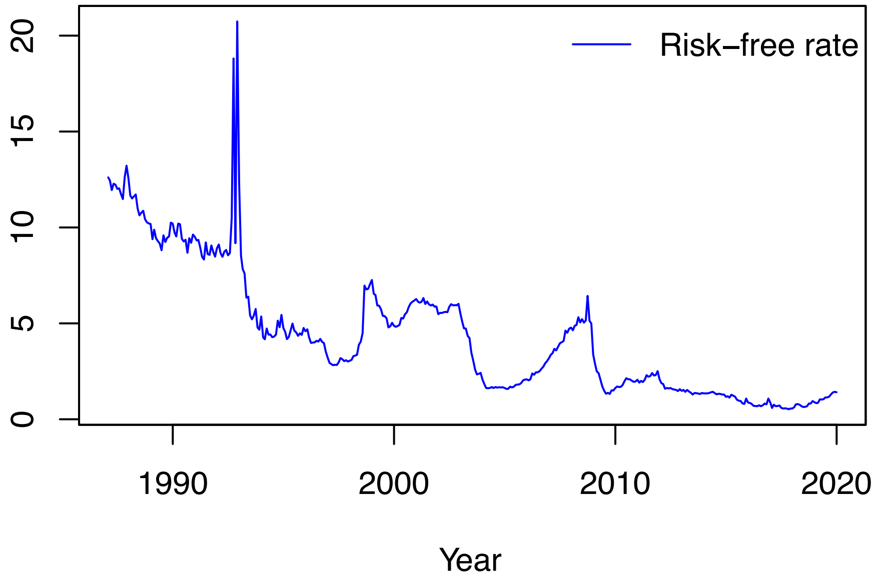
**Table A.II: Mutual Fund Descriptive Statistics (2/2)**

| Name | Obs | Mean | Std. dev. | Kurtosis | Skew | Max | Min |
|---|---|---|---|---|---|---|---|
| Globus Aktiv | 88 | 0.013 | 0.085 | 0.278 | -0.299 | 0.236 | -0.226 |
| Globus Norge | 103 | 0.006 | 0.085 | 0.315 | -0.346 | 0.223 | -0.234 |
| Globus Norge II | 95 | 0.010 | 0.082 | 0.326 | -0.236 | 0.231 | -0.229 |
| Handelsbanken Norge | 300 | 0.010 | 0.060 | 4.037 | -1.160 | 0.178 | -0.288 |
| Handelsbanken Norge A10 | 18 | 0.003 | 0.036 | 0.139 | -1.079 | 0.049 | -0.085 |
| Holberg Norge | 229 | 0.010 | 0.057 | 1.655 | -0.512 | 0.159 | -0.239 |
| K-IPA Aksjefond | 37 | 0.010 | 0.066 | 1.812 | -0.928 | 0.123 | -0.218 |
| KLP Aksjeinvest | 97 | 0.004 | 0.061 | 1.572 | -0.767 | 0.149 | -0.222 |
| KLP AksjeNorge | 250 | 0.010 | 0.059 | 3.192 | -0.901 | 0.176 | -0.298 |
| Landkreditt Norge | 122 | 0.006 | 0.059 | 2.058 | -0.728 | 0.171 | -0.207 |
| Landkreditt Utbytte | 83 | 0.012 | 0.021 | 0.354 | -0.744 | 0.047 | -0.047 |
| Landkreditt Utbytte I | 19 | 0.009 | 0.021 | -0.563 | -0.360 | 0.042 | -0.038 |
| NB-Aksjefond | 207 | 0.008 | 0.065 | 2.088 | -0.938 | 0.182 | -0.248 |
| Nordea Avkastning | 396 | 0.010 | 0.063 | 2.673 | -0.870 | 0.207 | -0.276 |
| Nordea Barnespar | 47 | -0.002 | 0.061 | -0.433 | -0.353 | 0.114 | -0.164 |
| Nordea Kapital | 298 | 0.011 | 0.058 | 2.879 | -1.007 | 0.167 | -0.257 |
| Nordea Kapital II | 84 | 0.012 | 0.065 | -0.262 | -0.461 | 0.134 | -0.175 |
| Nordea Kapital III | 70 | 0.011 | 0.067 | -0.327 | -0.551 | 0.133 | -0.175 |
| Nordea Norge Pluss | 105 | 0.008 | 0.038 | 1.094 | -0.643 | 0.121 | -0.111 |
| Nordea Norge Verdi | 287 | 0.010 | 0.055 | 2.624 | -0.863 | 0.152 | -0.245 |
| Nordea SMB | 213 | 0.006 | 0.068 | 0.507 | -0.230 | 0.183 | -0.232 |
| Nordea SMB II | 70 | -0.011 | 0.076 | 0.044 | 0.162 | 0.187 | -0.191 |
| Nordea Vekst | 337 | 0.009 | 0.066 | 1.820 | -0.846 | 0.195 | -0.262 |
| ODIN Norge | 331 | 0.013 | 0.060 | 2.383 | -0.425 | 0.228 | -0.241 |
| ODIN Norge A | 50 | 0.009 | 0.028 | 1.368 | -1.158 | 0.047 | -0.086 |
| ODIN Norge B | 50 | 0.009 | 0.028 | 1.384 | -1.162 | 0.047 | -0.086 |
| ODIN Norge D | 50 | 0.009 | 0.028 | 1.376 | -1.161 | 0.047 | -0.086 |
| ODIN Norge II | 139 | 0.010 | 0.056 | 3.021 | -0.983 | 0.136 | -0.240 |
| Orkla Finans 30 | 162 | 0.015 | 0.063 | 1.427 | -0.702 | 0.147 | -0.262 |
| Pareto Aksje Norge | 220 | 0.011 | 0.054 | 3.474 | -0.832 | 0.161 | -0.261 |
| PLUSS Aksje | 277 | 0.009 | 0.059 | 2.283 | -0.718 | 0.176 | -0.255 |
| PLUSS Markedsverdi | 300 | 0.010 | 0.056 | 3.173 | -0.973 | 0.160 | -0.250 |
| Postbanken Aksjevekst | 97 | 0.006 | 0.068 | 0.088 | -0.390 | 0.148 | -0.197 |
| RF Aksjefond | 116 | 0.009 | 0.062 | 1.200 | -0.724 | 0.135 | -0.238 |
| RF-Plussfond | 54 | 0.014 | 0.072 | -0.616 | -0.350 | 0.145 | -0.171 |
| Sbanken Framgang Sammen | 47 | 0.011 | 0.027 | 0.654 | -0.708 | 0.067 | -0.072 |
| SEB Norge LU | 67 | -0.004 | 0.073 | 1.112 | -0.632 | 0.156 | -0.261 |
| Skandia Horisont | 97 | 0.010 | 0.064 | 1.046 | -0.747 | 0.162 | -0.215 |
| Skandia SMB Norge | 97 | 0.001 | 0.069 | 2.326 | -0.994 | 0.138 | -0.273 |
| SR-Bank Norge A | 12 | 0.014 | 0.029 | -0.901 | -0.429 | 0.052 | -0.046 |
| SR-Bank Norge B | 12 | 0.014 | 0.029 | -0.900 | -0.429 | 0.052 | -0.046 |
| Storebrand Aksje Innland | 282 | 0.009 | 0.058 | 3.033 | -1.013 | 0.154 | -0.265 |
| Storebrand AksjeSpar | 226 | 0.006 | 0.043 | 1.258 | -0.889 | 0.103 | -0.140 |
| Storebrand Norge | 396 | 0.011 | 0.062 | 2.454 | -0.886 | 0.173 | -0.288 |
| Storebrand Norge A | 43 | 0.019 | 0.071 | -0.368 | -0.498 | 0.146 | -0.172 |
| Storebrand Norge Fossilfri | 33 | 0.009 | 0.020 | 1.091 | -0.851 | 0.045 | -0.053 |
| Storebrand Norge I | 237 | 0.009 | 0.059 | 3.153 | -0.992 | 0.149 | -0.286 |
| Storebrand Norge Institusjon | 39 | 0.007 | 0.042 | 0.465 | -0.513 | 0.099 | -0.097 |
| Storebrand Optima Norge | 221 | 0.010 | 0.061 | 2.981 | -0.985 | 0.146 | -0.293 |
| Storebrand Vekst | 328 | 0.013 | 0.069 | 3.664 | 0.010 | 0.367 | -0.301 |
| Storebrand Verdi | 265 | 0.009 | 0.058 | 3.137 | -0.960 | 0.135 | -0.265 |
| Storebrand Verdi N | 22 | 0.006 | 0.030 | -0.403 | -0.497 | 0.059 | -0.056 |
| Terra Norge | 187 | 0.008 | 0.071 | 1.412 | -0.746 | 0.188 | -0.262 |
| VÅR Aksjefond | 39 | 0.007 | 0.071 | 3.158 | -1.141 | 0.115 | -0.261 |

## Appendix B

**Figure B.I: Monthly Risk-free Rate**

The figure displays a plot of the risk-free rate (NIBOR) for the entire sample period 1987-2019.



## Appendix C

**Table C.I: Individual Mutual Fund Alpha and Factor Loadings 1/2**

The tables C.I and C.II report the characteristics of each fund's risk factors in our sample of 107 Norwegian mutual funds generated by running regression analysis on each fund. The funds are sorted alphabetically, and alphas are annualized. Column 2-4 report factor loadings of the risk factors MKT. SMB. HML and PR1YR, respectively. Adjusted R2 is reported in column 7.

| Name | $\beta^{MKT}$ | $\beta^{SMB}$ | $\beta^{HML}$ | $\beta^{PR1YR}$ | $R^2$ adjusted |
|---|---|---|---|---|---|
| ABIF Norge ++ | 1.041 | -0.069 | -0.045 | -0.110 | 0.956 |
| Alfred Berg Aksjef Norge | 1.006 | 0.071 | -0.001 | -0.036 | 0.950 |
| Alfred Berg Aksjespar | 1.071 | 0.110 | -0.011 | 0.017 | 0.918 |
| Alfred Berg Aktiv | 1.137 | 0.269 | -0.179 | 0.033 | 0.861 |
| Alfred Berg Aktiv II | 1.089 | 0.312 | -0.183 | -0.064 | 0.868 |
| Alfred Berg Gambak | 1.097 | 0.311 | -0.274 | 0.106 | 0.797 |
| Alfred Berg Humanfond | 0.992 | -0.015 | -0.092 | -0.068 | 0.909 |
| Alfred Berg N. Pensjon | 1.066 | 0.066 | -0.034 | -0.008 | 0.934 |
| Alfred Berg Norge | 1.058 | 0.027 | -0.084 | -0.090 | 0.951 |
| Alfred Berg Norge +_gml | 1.052 | 0.045 | -0.081 | -0.059 | 0.952 |
| Alfred Berg Norge Classic | 1.046 | 0.022 | -0.039 | -0.006 | 0.939 |
| Alfred Berg Norge Etisk | 1.053 | 0.029 | -0.158 | -0.136 | 0.939 |
| Alfred Berg Norge Inst | 0.844 | -0.016 | -0.078 | 0.117 | 0.840 |
| Alfred Berg Vekst | 1.157 | 0.308 | -0.106 | 0.159 | 0.796 |
| Arctic Norwegian Equities Class A | 0.843 | 0.054 | -0.102 | 0.170 | 0.750 |
| Arctic Norwegian Equities Class B | 0.922 | 0.061 | -0.104 | 0.176 | 0.799 |
| Arctic Norwegian Equities Class D | 0.823 | 0.030 | -0.084 | 0.180 | 0.764 |
| Arctic Norwegian Equities Class I | 0.916 | 0.061 | -0.104 | 0.177 | 0.801 |
| Atlas Norge | 1.126 | 0.140 | -0.266 | -0.025 | 0.854 |
| Banco Norge | 1.051 | 0.129 | -0.179 | -0.185 | 0.922 |
| C WorldWide Norge | 1.009 | -0.021 | -0.156 | 0.031 | 0.921 |
| Carnegie Askje Norge | 1.024 | 0.002 | -0.157 | 0.001 | 0.930 |
| Danske Invest Aktiv Formuesf. A | 0.777 | 0.369 | 0.386 | 0.329 | 0.686 |
| Danske Invest Norge Aksj. Inst 1 | 0.956 | -0.041 | -0.034 | -0.091 | 0.917 |
| Danske Invest Norge Aksj. Inst 2 | 0.956 | -0.045 | -0.024 | -0.031 | 0.910 |
| Danske Invest Norge I | 0.988 | 0.001 | -0.049 | -0.102 | 0.902 |
| Danske Invest Norge II | 0.997 | 0.008 | -0.041 | -0.103 | 0.906 |
| Danske Invest Norge Vekst | 1.085 | 0.411 | -0.229 | 0.017 | 0.772 |
| Delphi Norge | 1.163 | 0.300 | -0.228 | -0.029 | 0.838 |
| Delphi Vekst | 1.113 | 0.365 | -0.291 | -0.090 | 0.842 |
| DNB Norge | 1.004 | -0.046 | -0.031 | -0.063 | 0.964 |
| DNB Norge (Avanse I) | 0.939 | 0.001 | -0.049 | -0.092 | 0.919 |
| DNB Norge (Avanse II) | 0.985 | -0.005 | -0.058 | -0.067 | 0.941 |
| DNB Norge (I) | 0.997 | 0.052 | -0.022 | -0.036 | 0.737 |
| DNB Norge (III) | 1.006 | -0.028 | -0.038 | -0.064 | 0.963 |
| DNB Norge (IV) | 1.015 | -0.025 | -0.066 | -0.051 | 0.959 |
| DNB Norge Selektiv (II) | 0.862 | 0.332 | 0.125 | -0.138 | 0.930 |
| DNB Norge Selektiv (III) | 1.008 | -0.032 | -0.060 | -0.057 | 0.950 |
| DnB Real-Vekst | 1.027 | 0.052 | -0.068 | -0.052 | 0.936 |
| DNB SMB | 0.994 | 0.051 | -0.036 | -0.010 | 0.463 |
| DNB Norge R | 1.189 | 0.472 | -0.119 | -0.190 | 0.789 |
| Eika Norge | 1.026 | 0.125 | -0.036 | -0.098 | 0.886 |
| Eika SMB | 0.986 | 0.181 | -0.040 | -0.216 | 0.854 |
| FIRST Generator | 1.463 | 0.326 | -0.069 | 0.003 | 0.728 |
| FIRST Norge Fokus | 0.726 | -0.332 | -0.185 | -0.031 | 0.772 |
| Fokus Barnespar | 0.975 | 0.039 | -0.024 | -0.271 | 0.834 |
| Fondsfinans Aktiv II | 0.957 | -0.072 | -0.003 | -0.167 | 0.901 |
| Fondsfinans Norge | 1.025 | 0.073 | -0.063 | -0.124 | 0.868 |
| FORTE Norge | 1.056 | 0.071 | -0.094 | 0.034 | 0.700 |
| FORTE Trønder | 0.802 | 0.028 | -0.041 | 0.048 | 0.466 |
| GAMBAK Oppkjøp | 0.488 | 0.263 | -0.141 | 0.414 | 0.684 |
| GJENSIDIGE AksjeSpar | 0.954 | 0.047 | 0.029 | 0.000 | 0.931 |
| GJENSIDIGE Invest | 0.998 | 0.164 | 0.093 | 0.016 | 0.942 |

**Table C.II: Individual Mutual Fund Alpha and Factor Loadings 2/2**

| Name | ßMKT | ßMKT | ßMKT | ßMKT | $R^2$ adjusted |
|---|---|---|---|---|---|
| Globus Aktiv | 1.184 | 0.225 | -0.214 | -0.316 | 0.819 |
| Globus Norge | 1.157 | 0.281 | -0.206 | -0.348 | 0.838 |
| Globus Norge II | 1.171 | 0.251 | -0.220 | -0.329 | 0.812 |
| Handelsbanken Norge | 1.032 | 0.011 | -0.074 | -0.007 | 0.903 |
| Handelsbanken Norge A10 | 1.036 | -0.088 | -0.084 | 0.182 | 0.898 |
| Holberg Norge | 1.002 | 0.239 | -0.101 | -0.098 | 0.840 |
| K-IPA Aksjefond | 0.973 | 0.156 | 0.097 | 0.003 | 0.851 |
| KLP Aksjeinvest | 0.950 | 0.007 | -0.040 | -0.097 | 0.902 |
| KLP AksjeNorge | 1.018 | -0.015 | -0.048 | -0.057 | 0.917 |
| Landkreditt Norge | 0.947 | 0.108 | -0.014 | -0.148 | 0.831 |
| Landkreditt Utbytte | 0.535 | 0.067 | 0.034 | 0.081 | 0.505 |
| Landkreditt Utbytte I | 0.528 | 0.155 | 0.026 | 0.012 | 0.598 |
| NB-Aksjefond | 0.996 | 0.068 | -0.016 | -0.158 | 0.921 |
| Nordea Avkastning | 0.961 | -0.006 | -0.070 | -0.068 | 0.831 |
| Nordea Barnespar | 0.981 | -0.040 | -0.052 | -0.009 | 0.921 |
| Nordea Kapital | 1.017 | 0.022 | -0.079 | -0.060 | 0.930 |
| Nordea Kapital II | 1.031 | -0.116 | -0.065 | -0.095 | 0.915 |
| Nordea Kapital III | 1.035 | -0.010 | -0.082 | -0.166 | 0.939 |
| Nordea Norge Pluss | 1.066 | 0.123 | -0.084 | 0.029 | 0.840 |
| Nordea Norge Verdi | 0.941 | 0.157 | -0.036 | -0.115 | 0.865 |
| Nordea SMB | 1.102 | 0.517 | -0.090 | -0.146 | 0.828 |
| Nordea SMB II | 1.042 | 0.553 | -0.130 | -0.088 | 0.781 |
| Nordea Vekst | 1.006 | 0.031 | -0.038 | -0.067 | 0.911 |
| ODIN Norge | 1.000 | 0.285 | 0.058 | -0.086 | 0.789 |
| ODIN Norge A | 0.808 | 0.013 | -0.049 | -0.024 | 0.771 |
| ODIN Norge B | 0.809 | 0.013 | -0.050 | -0.024 | 0.772 |
| ODIN Norge D | 0.808 | 0.012 | -0.049 | -0.024 | 0.771 |
| ODIN Norge II | 0.975 | 0.298 | -0.050 | -0.062 | 0.816 |
| Orkla Finans 30 | 1.049 | 0.142 | -0.048 | -0.088 | 0.913 |
| Pareto Aksje Norge | 0.950 | 0.183 | 0.004 | -0.037 | 0.837 |
| PLUSS Aksje | 0.972 | -0.022 | -0.078 | -0.076 | 0.890 |
| PLUSS Markedsverdi | 0.947 | -0.107 | -0.036 | -0.065 | 0.936 |
| Postbanken Aksjevekst | 1.016 | 0.046 | -0.184 | -0.096 | 0.917 |
| RF Aksjefond | 0.958 | 0.022 | -0.057 | -0.126 | 0.917 |
| RF-Plussfond | 1.111 | 0.199 | -0.300 | -0.193 | 0.866 |
| Sbanken Framgang Sammen | 0.889 | -0.039 | -0.036 | 0.065 | 0.839 |
| SEB Norge LU | 1.066 | 0.035 | -0.079 | -0.059 | 0.919 |
| Skandia Horisont | 1.046 | 0.212 | -0.091 | 0.027 | 0.858 |
| Skandia SMB Norge | 1.066 | 0.429 | -0.134 | -0.119 | 0.817 |
| SR-Bank Norge A | 1.303 | 0.273 | 0.034 | 0.161 | 0.897 |
| SR-Bank Norge B | 1.303 | 0.273 | 0.034 | 0.161 | 0.897 |
| Storebrand Aksje Innland | 1.009 | -0.035 | -0.043 | -0.027 | 0.970 |
| Storebrand AksjeSpar | 0.655 | 0.055 | -0.142 | -0.101 | 0.717 |
| Storebrand Norge | 0.982 | 0.001 | -0.038 | -0.045 | 0.890 |
| Storebrand Norge A | 1.063 | 0.034 | -0.130 | -0.199 | 0.923 |
| Storebrand Norge Fossilfri | 0.469 | -0.102 | -0.113 | 0.029 | 0.547 |
| Storebrand Norge I | 1.037 | 0.008 | -0.060 | -0.094 | 0.944 |
| Storebrand Norge Institusjon | 0.984 | 0.034 | -0.069 | 0.046 | 0.914 |
| Storebrand Optima Norge | 1.037 | 0.015 | -0.063 | -0.096 | 0.924 |
| Storebrand Vekst | 1.045 | 0.247 | -0.402 | -0.032 | 0.711 |
| Storebrand Verdi | 0.987 | -0.051 | 0.106 | 0.013 | 0.936 |
| Storebrand Verdi N | 0.836 | 0.022 | 0.066 | -0.066 | 0.931 |
| Terra Norge | 1.060 | 0.115 | -0.164 | -0.101 | 0.920 |
| VÅR Aksjefond | 1.106 | 0.090 | 0.213 | 0.063 | 0.898 |

## Appendix D

**Table D.I: Individual Mutual Fund Bootstrap Results 1/2**

The tables D.I and D.II report the bootstrapped results for each fund in our 107 Norwegian mutual funds sample. The funds are sorted alphabetically, and alphas are annualized—columns 2-6 report the alpha, t-statistic of alpha, parametric p-value, and bootstrapped p-value. The statistics are based on 10,000 bootstrap resamples.

| Name | Alpha | T-statistic of Alpha | Parametric P-value | Bootstrap P-value |
|---|---|---|---|---|
| ABIF Norge ++ | 0.698 | 0.29 | 0.39 | 0.72 |
| Alfred Berg Aksjef Norge | -3.324 | -2.03 | 0.02 | 0.02 |
| Alfred Berg Aksjespar | -4.981 | -2.14 | 0.02 | 0.02 |
| Alfred Berg Aktiv | -1.705 | -0.92 | 0.18 | 0.00 |
| Alfred Berg Aktiv II | -2.928 | -1.20 | 0.12 | 0.00 |
| Alfred Berg Gambak | -0.382 | -0.19 | 0.42 | 0.02 |
| Alfred Berg Humanfond | 0.312 | 0.21 | 0.42 | 0.84 |
| Alfred Berg N. Pensjon | -3.494 | -1.24 | 0.11 | 0.00 |
| Alfred Berg Norge | 1.371 | 0.85 | 0.20 | 0.49 |
| Alfred Berg Norge +_gml | -0.007 | -0.01 | 0.50 | 0.06 |
| Alfred Berg Norge Classic | -0.945 | -0.93 | 0.18 | 0.00 |
| Alfred Berg Norge Etisk | -1.234 | -0.68 | 0.25 | 0.00 |
| Alfred Berg Norge Inst | 1.302 | 0.66 | 0.26 | 0.50 |
| Alfred Berg Vekst | -8.954 | -1.72 | 0.04 | 0.00 |
| Arctic Norwegian Equities Class A | -2.916 | -1.30 | 0.10 | 0.00 |
| Arctic Norwegian Equities Class B | -2.987 | -1.42 | 0.08 | 0.01 |
| Arctic Norwegian Equities Class D | -1.536 | -0.69 | 0.25 | 0.00 |
| Arctic Norwegian Equities Class I | -2.857 | -1.37 | 0.09 | 0.01 |
| Atlas Norge | -1.913 | -0.91 | 0.18 | 0.00 |
| Banco Norge | -2.111 | -0.50 | 0.31 | 0.00 |
| C WorldWide Norge | 0.922 | 0.74 | 0.23 | 0.44 |
| Carnegie Askje Norge | 1.782 | 1.15 | 0.13 | 0.63 |
| Danske Invest Aktiv Formuesf. A | -19.062 | -1.89 | 0.03 | 0.01 |
| Danske Invest Norge Aksj. Inst 1 | 3.024 | 2.23 | 0.01 | 0.81 |
| Danske Invest Norge Aksj. Inst 2 | 3.263 | 1.94 | 0.03 | 0.21 |
| Danske Invest Norge I | 0.723 | 0.55 | 0.29 | 0.58 |
| Danske Invest Norge II | 1.394 | 1.07 | 0.14 | 0.61 |
| Danske Invest Norge Vekst | -0.742 | -0.33 | 0.37 | 0.01 |
| Delphi Norge | -0.231 | -0.12 | 0.45 | 0.05 |
| Delphi Vekst | -1.993 | -0.74 | 0.23 | 0.00 |
| DNB Norge | -1.211 | -1.44 | 0.07 | 0.03 |
| DNB Norge (Avanse I) | -0.998 | -0.80 | 0.21 | 0.00 |
| DNB Norge (Avanse II) | -1.721 | -1.53 | 0.06 | 0.01 |
| DNB Norge (I) | -0.192 | -0.07 | 0.47 | 0.03 |
| DNB Norge (III) | -0.063 | -0.07 | 0.47 | 0.04 |
| DNB Norge (IV) | 0.170 | 0.16 | 0.44 | 0.89 |
| DNB Norge Selektiv (II) | 6.106 | 1.11 | 0.13 | 0.60 |
| DNB Norge Selektiv (III) | 0.577 | 0.50 | 0.31 | 0.56 |
| DnB Real-Vekst | -0.384 | -0.36 | 0.36 | 0.01 |
| DNB SMB | -2.299 | -0.36 | 0.36 | 0.01 |
| DNB Norge R | 1.911 | 0.71 | 0.24 | 0.44 |
| Eika Norge | 1.711 | 0.97 | 0.17 | 0.56 |
| Eika SMB | -1.228 | -0.52 | 0.30 | 0.00 |
| FIRST Generator | -3.576 | -0.91 | 0.18 | 0.00 |
| FIRST Norge Fokus | 10.946 | 2.19 | 0.01 | 0.54 |
| Fokus Barnespar | -11.889 | -1.67 | 0.05 | 0.00 |
| Fondsfinans Aktiv II | -2.485 | -0.65 | 0.26 | 0.00 |
| Fondsfinans Norge | 3.776 | 1.94 | 0.03 | 0.38 |
| FORTE Norge | -1.044 | -0.33 | 0.37 | 0.00 |
| FORTE Trønder | 6.177 | 1.43 | 0.08 | 0.62 |
| GAMBAK Oppkjøp | -18.620 | -1.81 | 0.04 | 0.01 |
| GJENSIDIGE AksjeSpar | -4.276 | -2.45 | 0.01 | 0.00 |
| GJENSIDIGE Invest | -0.954 | 0.11 | 0.19 | 0.23 |

**Table D.II: Individual Mutual Fund Bootstrap Results 2/2**

| Name | Alpha | T-statistic of Alpha | Parametric P-value | Bootstrap P-value |
|---|---|---|---|---|
| Globus Aktiv | -6.132 | -1.21 | 0.11 | 0.00 |
| Globus Norge | -8.535 | -1.99 | 0.02 | 0.01 |
| Globus Norge II | -8.341 | -1.73 | 0.04 | 0.01 |
| Handelsbanken Norge | 0.082 | 0.06 | 0.48 | 0.93 |
| Handelsbanken Norge A10 | -3.206 | -0.84 | 0.20 | 0.00 |
| Holberg Norge | 1.145 | 0.59 | 0.28 | 0.62 |
| K-IPA Aksjefond | 4.722 | 0.90 | 0.18 | 0.54 |
| KLP Aksjeinvest | -2.444 | -0.97 | 0.17 | 0.00 |
| KLP AksjeNorge | 0.206 | 0.15 | 0.44 | 0.87 |
| Landkreditt Norge | 3.186 | 1.15 | 0.12 | 0.72 |
| Landkreditt Utbytte | 5.384 | 2.15 | 0.02 | 0.32 |
| Landkreditt Utbytte I | 7.616 | 1.82 | 0.03 | 0.11 |
| NB-Aksjefond | -1.359 | -0.85 | 0.20 | 0.00 |
| Nordea Avkastning | 0.483 | 0.29 | 0.38 | 0.77 |
| Nordea Barnespar | -3.020 | -0.94 | 0.17 | 0.00 |
| Nordea Kapital | 0.933 | 0.81 | 0.21 | 0.42 |
| Nordea Kapital II | -0.709 | -0.26 | 0.40 | 0.01 |
| Nordea Kapital III | -3.227 | -1.24 | 0.11 | 0.00 |
| Nordea Norge Pluss | -0.810 | -0.38 | 0.35 | 0.01 |
| Nordea Norge Verdi | 1.349 | 0.88 | 0.19 | 0.49 |
| Nordea SMB | -6.439 | -2.63 | 0.00 | 0.01 |
| Nordea SMB II | -16.925 | -3.18 | 0.00 | 0.02 |
| Nordea Vekst | -1.771 | -1.31 | 0.10 | 0.00 |
| ODIN Norge | 1.066 | 0.55 | 0.29 | 0.65 |
| ODIN Norge A | 1.551 | 0.54 | 0.29 | 0.52 |
| ODIN Norge B | 1.281 | 0.45 | 0.33 | 0.56 |
| ODIN Norge D | 1.307 | 0.45 | 0.32 | 0.61 |
| ODIN Norge II | -0.388 | -0.15 | 0.44 | 0.04 |
| Orkla Finans 30 | -2.070 | -1.06 | 0.14 | 0.00 |
| Pareto Aksje Norge | 1.803 | 0.95 | 0.17 | 0.49 |
| PLUSS Aksje | 1.245 | 0.82 | 0.21 | 0.46 |
| PLUSS Markedsverdi | 1.950 | 1.83 | 0.03 | 0.20 |
| Postbanken Aksjevekst | -2.966 | -1.17 | 0.12 | 0.00 |
| RF Aksjefond | -2.321 | -1.09 | 0.14 | 0.00 |
| RF-Plussfond | -7.010 | -1.43 | 0.08 | 0.01 |
| Sbanken Framgang Sammen | -1.007 | -0.41 | 0.34 | 0.01 |
| SEB Norge LU | -1.682 | -0.53 | 0.30 | 0.00 |
| Skandia Horisont | 0.260 | 0.08 | 0.47 | 0.93 |
| Skandia SMB Norge | -12.248 | -3.22 | 0.00 | 0.17 |
| SR-Bank Norge A | -7.080 | -1.05 | 0.15 | 0.00 |
| SR-Bank Norge B | -7.067 | -1.05 | 0.15 | 0.00 |
| Storebrand Aksje Innland | 0.230 | 0.30 | 0.38 | 0.82 |
| Storebrand AksjeSpar | -0.204 | -0.10 | 0.46 | 0.04 |
| Storebrand Norge | 0.974 | 0.74 | 0.23 | 0.51 |
| Storebrand Norge A | -2.274 | -0.56 | 0.29 | 0.00 |
| Storebrand Norge Fossilfri | 4.182 | 1.24 | 0.11 | 0.76 |
| Storebrand Norge I | 1.600 | 1.36 | 0.09 | 0.65 |
| Storebrand Norge Institusjon | -3.565 | -1.33 | 0.09 | 0.01 |
| Storebrand Optima Norge | 1.717 | 1.19 | 0.12 | 0.76 |
| Storebrand Vekst | 0.062 | 0.02 | 0.49 | 0.94 |
| Storebrand Verdi | 1.133 | 0.99 | 0.16 | 0.61 |
| Storebrand Verdi N | 2.323 | 1.02 | 0.15 | 0.63 |
| Terra Norge | -1.280 | -0.69 | 0.24 | 0.00 |
| VÅR Aksjefond | 1.909 | 0.42 | 0.34 | 0.55 |

## Appendix E

**Table E.I: Time-Series Dependence: Cross-sectional Mutual Fund Alphas**

Based on stationary bootstrap results with different lengths for the full period 1987-2019, the table provides the funds' cross-sectional performance measure results. The table is divided into four panels, each containing the results using different block lengths. Panel A reports a block length of one monthly return and panel B-D reports for block lengths 2, 4, and 10. Row 1-3 in both panels reports the same statistic where row 1 reports the estimated t-statistic of alpha. Row 2 displays the cross-sectionally annualized associated alpha for the t-statistic, whereas row 3 displays the parametric p-values of the t-statistic. The statistics are based on 10,000 bootstrap resamples and are ranked on their t-statistic of alpha in both panels.

| | Bottom | 2nd | 3rd | Bottom 5% | Bottom 10% | Top 10% | Top 5% | 3rd | 2nd | Top |
|---|---|---|---|---|---|---|---|---|---|---|
| **Panel A: Fund Ranked on t-statistic Four-Factor Model Alphas: Block length One monthly return** | | | | | | | | | | |
| T-alpha | -3.22 | -3.18 | -2.96 | -2.45 | -1.73 | 1.19 | 1.94 | 2.15 | 2.19 | 2.23 |
| Bootstrapped p-value | 0.17 | 0.02 | 0.00 | 0.00 | 0.01 | 0.76 | 0.21 | 0.33 | 0.55 | 0.81 |
| Parametric p-value | 0.00 | 0.00 | 0.00 | 0.01 | 0.04 | 0.12 | 0.03 | 0.02 | 0.01 | 0.01 |
| **Panel B: Fund Ranked on t-statistic Four-Factor Model Alphas: Block length 2 monthly return** | | | | | | | | | | |
| T-alpha | -3.22 | -3.18 | -2.96 | -2.45 | -1.73 | 1.19 | 1.94 | 2.15 | 2.19 | 2.23 |
| Bootstrapped p-value | 0.18 | 0.02 | 0.00 | 0.00 | 0.01 | 0.72 | 0.19 | 0.31 | 0.53 | 0.80 |
| Parametric p-value | 0.00 | 0.00 | 0.00 | 0.01 | 0.04 | 0.12 | 0.03 | 0.02 | 0.01 | 0.01 |
| **Panel C: Fund Ranked on t-statistic Four-Factor Model Alphas: Block length 4 monthly return** | | | | | | | | | | |
| T-alpha | -3.22 | -3.18 | -2.96 | -2.45 | -1.73 | 1.19 | 1.94 | 2.15 | 2.19 | 2.23 |
| Bootstrapped p-value | 0.19 | 0.02 | 0.01 | 0.00 | 0.01 | 0.70 | 0.18 | 0.30 | 0.52 | 0.80 |
| Parametric p-value | 0.00 | 0.00 | 0.00 | 0.00 | 0.01 | 0.04 | 0.02 | 0.02 | 0.01 | 0.01 |
| **Panel D: Fund Ranked on t-statistic Four-Factor Model Alphas: Block length 10 monthly return** | | | | | | | | | | |
| T-alpha | -3.22 | -3.18 | -2.96 | -2.45 | -1.73 | 1.19 | 1.94 | 2.15 | 2.19 | 2.23 |
| Bootstrapped p-value | 0.18 | 0.02 | 0.00 | 0.00 | 0.01 | 0.60 | 0.13 | 0.26 | 0.48 | 0.78 |
| Parametric p-value | 0.00 | 0.00 | 0.00 | 0.01 | 0.04 | 0.12 | 0.03 | 0.02 | 0.01 | 0.01 |

**Table E.II: Factor and Residual Resampling**

The table provides the results for the performance measure in the cross-section using a minimum of 24 observations of resampling factors and residuals for the full period 1987-2019. Panel A reports our baseline bootstrap, while panel B contains the resampling of factors and residuals results. Row 1-3 in both panels reports the same statistic where row 1 reports the estimated t-statistic of alpha. Row 2 displays the cross-sectionally annualized associated alpha for the t-statistic, whereas row 3 displays the parametric p-values of the t-statistic. The statistics are based on 10,000 bootstrap resamples and are ranked on their t-statistic of alpha in both panels.

| | Bottom | 2nd | 3rd | Bottom 5% | Bottom 10% | Top 10% | Top 5% | 3rd | 2nd | Top |
|---|---|---|---|---|---|---|---|---|---|---|
| **Panel A: Baseline Bootstrap** | | | | | | | | | | |
| T-alpha | -3.22 | -3.18 | -2.96 | -2.45 | -1.73 | 1.19 | 1.94 | 2.15 | 2.19 | 2.23 |
| Bootstrapped p-value | 0.17 | 0.02 | 0.00 | 0.00 | 0.01 | 0.76 | 0.21 | 0.33 | 0.55 | 0.81 |
| Parametric p-value | 0.00 | 0.00 | 0.00 | 0.01 | 0.04 | 0.12 | 0.03 | 0.02 | 0.01 | 0.01 |
| **Panel B: Residual and Factorial Resampling N=24** | | | | | | | | | | |
| T-alpha | -3.22 | -3.18 | -2.96 | -2.45 | -1.72 | 1.15 | 1.83 | 1.94 | 2.15 | 2.23 |
| Bootstrapped p-value | 0.13 | 0.01 | 0.00 | 0.00 | 0.02 | 0.80 | 0.26 | 0.51 | 0.50 | 0.75 |
| Parametric p-value | 0.00 | 0.00 | 0.00 | 0.01 | 0.04 | 0.12 | 0.03 | 0.03 | 0.02 | 0.01 |

**Table E.III: Cross-sectional Bootstrap**

The table provides the performance measure results in the cross-section using joint resampling of fund and factor returns for the full period 1987-2019. Panel A reports the baseline bootstrap, and panel B reports the cross-sectional correlation in bootstrap residuals. Row 1-3 in both panels reports the same statistic where row 1 reports the estimated t-statistic of alpha. Row 2 displays the cross-sectionally annualized associated alpha for the t-statistic, whereas row 3 displays the parametric p-values of the t-statistic. The statistics are based on 10,000 bootstrap resamples and are ranked on their t-statistic of alpha in both panels.

| | Bottom | 2nd | 3rd | Bottom 5% | Bottom 10% | Top 10% | Top 5% | 3rd | 2nd | Top |
|---|---|---|---|---|---|---|---|---|---|---|
| **Panel A: Baseline Bootstrap** | | | | | | | | | | |
| T-alpha | -3.22 | -3.18 | -2.96 | -2.45 | -1.73 | 1.19 | 1.94 | 2.15 | 2.19 | 2.23 |
| Bootstrapped p-value | 0.17 | 0.02 | 0.00 | 0.00 | 0.01 | 0.76 | 0.21 | 0.33 | 0.55 | 0.81 |
| Parametric p-value | 0.00 | 0.00 | 0.00 | 0.01 | 0.04 | 0.12 | 0.03 | 0.02 | 0.01 | 0.01 |
| **Panel B: Cross-sectional Bootstrap** | | | | | | | | | | |
| T-alpha | -3.22 | -3.18 | -2.96 | -2.45 | -1.73 | 1.19 | 1.94 | 2.15 | 2.19 | 2.23 |
| Bootstrapped p-value | NA | NA | NA | NA | NA | 0.33 | 0.16 | 0.17 | 0.26 | 0.48 |
| Parametric p-value | 0.00 | 0.00 | 0.00 | 0.02 | 0.09 | 0.24 | 0.05 | 0.03 | 0.06 | 0.03 |

**Table E.IV: Portfolios of Funds**

The table provides the average statistic corresponding to portfolios in both left- and right tail distribution of alpha for 1987-2019. Panel A reports the baseline bootstrap in a different set-up than previously displayed, now reporting the top and bottom ten funds in our sample. The funds are ranked according to their t-statistic of alpha and bundled into portfolios, each consisting of two, three, and five funds. Panel B reports portfolios of 2 funds and makeup 53 funds. Panel C and D report 35 and 21 portfolios, holding 3 and 5 funds in each portfolio. The columns are the adjacent portfolios for each panel. For each panel, row 1 reports the estimated t-statistic of alpha. Row 2 displays the cross-sectionally annualized associated alpha for the t-statistic, whereas row 3 displays the parametric p-values of the t-statistic. The statistics are based on 10,000 bootstrap resamples and are ranked on their t-statistic of alpha in all panels.

| | Bot. | 2nd | 3rd | 4th | 5th | 6th | 7th | 8th | 9th | Bot. 10th | Top 10th | 9th | 8th | 7th | 6th | 5th | 4th | 3rd | 2nd | Top |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **Panel A: Portfolios of 2 funds. 53 total portfolios** | | | | | | | | | | | | | | | | | | | | |
| T-alpha | -3.72 | -3.19 | -2.18 | -2.13 | -1.95 | -1.76 | -1.71 | -1.69 | -1.56 | -1.52 | 1.20 | 1.22 | 1.23 | 1.24 | 1.37 | 1.45 | 1.80 | 2.00 | 2.40 | 2.43 |
| Bootstrapped p-value | NA | NA | NA | NA | NA | NA | NA | NA | 0.81 | 0.83 | 0.14 | 0.17 | 0.21 | 0.25 | 0.24 | 0.26 | 0.14 | 0.13 | 0.09 | 0.24 |
| Parametric p-value | 0.00 | 0.00 | 0.01 | 0.02 | 0.03 | 0.04 | 0.04 | 0.05 | 0.06 | 0.06 | 0.11 | 0.11 | 0.11 | 0.11 | 0.09 | 0.07 | 0.04 | 0.02 | 0.01 | 0.01 |
| **Panel B: Portfolios of 3 funds. 35 total portfolios** | | | | | | | | | | | | | | | | | | | | |
| T-alpha | -3.33 | -2.19 | -1.95 | -1.78 | -1.51 | -1.46 | -1.41 | -1.35 | -1.21 | -1.09 | 1.14 | 1.19 | 1.28 | 1.28 | 1.39 | 1.50 | 1.54 | 1.85 | 2.57 | 2.69 |
| Bootstrapped p-value | NA | NA | NA | 0.61 | 0.72 | 0.62 | 0.49 | 0.39 | 0.37 | 0.36 | 0.09 | 0.11 | 0.11 | 0.15 | 0.15 | 0.15 | 0.20 | 0.15 | 0.04 | 0.10 |
| Parametric p-value | 0.00 | 0.01 | 0.03 | 0.04 | 0.07 | 0.07 | 0.08 | 0.09 | 0.11 | 0.14 | 0.13 | 0.12 | 0.10 | 0.10 | 0.08 | 0.07 | 0.06 | 0.03 | 0.01 | 0.00 |
| **Panel C: Portfolios of 5 funds. 21 total portfolios** | | | | | | | | | | | | | | | | | | | | |
| T-alpha | -3.37 | -2.14 | -1.85 | -1.64 | -1.58 | -1.46 | -1.36 | -0.80 | -0.61 | -0.56 | -0.07 | 0.11 | 0.44 | 0.53 | 1.20 | 1.32 | 1.89 | 1.91 | 2.15 | 2.99 |
| Bootstrapped p-value | NA | NA | 0.37 | 0.45 | 0.36 | 0.27 | 0.21 | 0.42 | 0.43 | 0.36 | 0.52 | 0.45 | 0.31 | 0.34 | 0.09 | 0.10 | 0.03 | 0.07 | 0.08 | 0.04 |
| Parametric p-value | 0.00 | 0.02 | 0.03 | 0.05 | 0.06 | 0.07 | 0.09 | 0.21 | 0.27 | 0.29 | 0.47 | 0.46 | 0.33 | 0.30 | 0.12 | 0.09 | 0.03 | 0.03 | 0.02 | 0.00 |

**Table E.V: Length of Data Records**

The table provides the performance measure results in the cross-section with various minimum observation requirements for 1987-2019. Panel A reports the baseline bootstrap (based on 12 observations), panel B reports for a minimum of 24 observations, panel C for 36, and panel D for 60 observations. Row 1-3 in both panels reports the same statistic where row 1 reports the estimated t-statistic of alpha. Row 2 displays the cross-sectionally annualized associated alpha for the t-statistic, whereas row 3 displays the parametric p-values of the t-statistic. The statistics are based on 10,000 bootstrap resamples and are ranked on their t-statistic of alpha in both panels.

| | Bottom | 2nd | 3rd | Bottom 5% | Bottom 10% | Top 10% | Top 5% | 3rd | 2nd | Top |
|---|---|---|---|---|---|---|---|---|---|---|
| **Panel A: Baseline Bootstrap** | | | | | | | | | | |
| T-alpha | -3.22 | -3.18 | -2.96 | -2.45 | -1.73 | 1.19 | 1.94 | 2.15 | 2.19 | 2.23 |
| Bootstrapped p-value | 0.17 | 0.02 | 0.00 | 0.00 | 0.01 | 0.76 | 0.21 | 0.33 | 0.55 | 0.81 |
| Parametric p-value | 0.00 | 0.00 | 0.00 | 0.01 | 0.04 | 0.12 | 0.03 | 0.02 | 0.01 | 0.01 |
| **Panel B: 24 observation minimum per fund** | | | | | | | | | | |
| T-alpha | -3.22 | -3.18 | -2.96 | -2.45 | -1.72 | 1.15 | 1.83 | 1.94 | 2.15 | 2.23 |
| Bootstrapped p-value | 0.13 | 0.01 | 0.00 | 0.00 | 0.02 | 0.80 | 0.25 | 0.51 | 0.50 | 0.75 |
| Parametric p-value | 0.00 | 0.00 | 0.00 | 0.01 | 0.04 | 0.12 | 0.03 | 0.03 | 0.02 | 0.01 |
| **Panel C: 36 observation minimum per fund** | | | | | | | | | | |
| T-alpha | -3.22 | -3.18 | -2.96 | -2.45 | -1.81 | 1.15 | 1.94 | 1.94 | 2.15 | 2.23 |
| Bootstrapped p-value | 0.14 | 0.01 | 0.00 | 0.00 | 0.01 | 0.80 | 0.15 | 0.50 | 0.49 | 0.74 |
| Parametric p-value | 0.00 | 0.00 | 0.00 | 0.01 | 0.04 | 0.13 | 0.03 | 0.03 | 0.02 | 0.01 |
| **Panel D: 60 observation minimum per fund** | | | | | | | | | | |
| T-alpha | -3.22 | -3.18 | -2.96 | -2.63 | -1.99 | 1.19 | 1.94 | 1.94 | 2.15 | 2.23 |
| Bootstrapped p-value | 0.11 | 0.01 | 0.00 | 0.00 | 0.00 | 0.76 | 0.18 | 0.37 | 0.39 | 0.65 |
| Parametric p-value | 0.00 | 0.00 | 0.00 | 0.00 | 0.02 | 0.12 | 0.03 | 0.03 | 0.02 | 0.01 |

**Reflection Note 1, Niklas Bråthe**

Our topic, "The Paradox of Skill in Norwegian Mutual Funds", focuses on the bootstrap method of Kosowski et al. (2006). The general topic of evaluating luck versus skill among fund managers, and whether they can justify their cost, is heavily studied.

This thesis examines luck versus skill among 107 Norwegian Mutual Funds under the null hypothesis of no true performance. We replicated Kosowski et al. 's (2006) method as it is a highly acknowledged method in distinguishing luck from skill, generating p-values significantly different from a standard t-test. We conclude that the null cannot be rejected for the top performers as they did not generate statistically significant results at a 5% level of significance. The results were the opposite for the bottom performers as they generated significant results in most funds. The results indicate a lack of skill among the top performers; however, the bottom performers were not merely unlucky but also displayed a lack of skill. This is in keeping with the conclusion of Fama and French (2010) and substantiates previous research meaning that the results of studying foreign markets are somewhat transferable to the Norwegian finance markets.

Although the Norwegian economy has been performing well over the past year, especially compared to its neighbors, Norway is highly impressionable to international influence. This is a sign of the time as the world is becoming increasingly internationalized due to, amongst other things, technology and the internet of things (IoT). The financial industry is especially an international business as money invested is all over the world. Despite the funds in our sample comprising of at least 80% Norwegian stocks, no company is exempt from succumbing to the trends outside of Norway. We have not focused on which industry our sample funds are invested in; however, I find it relevant due the nature of the industry. The most significant trends in today's markets are arguably green finance and technology. The technology industry has had tremendous growth since the dot-com bubble in the late 1990s made tech companies some of the world's biggest. One of Norway's most prominent banks' (DNB Bank ASA) highest-performing mutual funds over the last decade has been DNB Technology, which is solely invested in the technology sector. Green finance is becoming increasingly important due to global warming and growing concern about the world's future. The financial industry is not exempt from this issue as it becomes more and more prominent in people's everyday lives. The asset management companies should arguably focus their products on products that contribute to making a sustainable future. All industries must obviously participate in the collective effort in saving the world. However, as the new generation of potential investors are growing up, they are exponentially more concerned with the environment than today's generations. This is a clear indication that to win over future customers, and asset management companies must address future customers' needs to succeed.

This thesis does not address a new topic; however, most literature and research are based on U.S. mutual funds resulting in only a handful of broad and extensive studies on the Norwegian mutual fund market. Our thesis provides substantiating evidence that supports a significant portion of previous studies. Fund managers in actively managed funds are all trying to identify that edge that will enable them to beat the market. If they can achieve this, they are considered skilled, and as our thesis, following Kosowski et al. (2006, concludes, the ones that can produce positive alphas are doing this by luck. Seeing as bottom performers lack stock-picking skill and luck, we suggest that fund managers assert their attention to building less expensive portfolios replicating the market. As index funds generate less profits than actively managed funds, it is more attractive for asset management companies to focus their time and resources on these products. Nevertheless, how does this affect industry and product innovation? The main drivers of innovation is arguably opportunities, problems, and constraints. Every industry experiences adversity, and one that affects everyone in the environmental issues. As I discuss this further under regarding responsibility, I will be focusing on other current drivers. Innovation in asset management and specifically mutual funds is identifying new ways the create value. We have argued a shift of focus towards index funds replicating the market at the lowest possible cost, and in light of our thesis, a relevant area is the use of technology. Technology and automation enable managers to make quicker desitions and even let computers and programs perform previously manual tasks. Technology also allows fund managers to produce more accurate market data, making market data more available to customers becoming increasingly transparent. Asset management companies should focus on using automation and cutting cost, and thereby generating higher returns net of cost.

An increasingly vital element in finance are ethics and responsibility. Investors are expected to take continuously greater responsibility regarding the environment, human rights, and sustainable solutions. The historical responsibility of companies has been towards generating profits for their shareholders. Now, Socially Responsible Investment (SRI) is becoming a part of more and more company's strategies and plans. In the wake of this shift, the emergence of SRI Funds has come to light, attempting to affect corporate practices in how they invest. Shareholders' advocacy is another element putting pressure in shifting to responsible investments but can be argued to be unimpactful as they may pursue other economic opportunities not fulfilling SRI's goal.

Nevertheless, SRI funds, green financing, and ethically sound investments have also been argued to make sense from a strictly financial perspective, often claiming to outperform conventional mutual funds. When selecting the funds in our thesis, we did not seek to identify whether funds can be categorized as SRI funds, but focused on what benefits investors financially. Specifically, in the first part, are the funds worth the investment. Most would argue that selling a product not fulfilling its promise is not a product one would purchase. In some cases, it can even be called a scam. The fund managers' responsibility is arguably to investors, shareholders (owners), and society as a whole. In line with our thesis, the discussion here is limited to focus on the investor. I would not argue that the funds in our sample fall in the category of scam; however, seeing that these products cannot fulfill their intent, I would argue that the investors' responsibility is towards the investor. The asset management companies should focus on providing financial products in line with current research, low-cost passive index funds.

We concluded in the thesis, as I have presented here, that low-cost passive index funds are the way forward. I would expand on that, focusing on the elements of internationalization, innovation, and responsibility, and suggest creating new financial products focusing on creating low-cost funds replicating the market based on sustainable investments using automation and relevant technology. This is arguably the right course, as it ensures all aspects equally crucial for future business.

Finally, to address the writing process, it has been challenging and very educational. The learning curve steepened as time progressed, and as the use of RStudio as an analytical tool and the bootstrap method was relatively new to us, it truly required us to immerse ourselves in the research. The work has given us a unique insight into the financial world that we believe will be of great value in future endeavors. We wish to extend our sincere gratitude to our supervisor Professor Valeriy Ivanovich Zakamulin, for comprehensive advice and guidance throughout writing this thesis.

**Reflection Note 2, Erlend André Bjerke**

Our topic, "The Paradox of Skill in Norwegian Mutual Funds, " focuses on the bootstrap method of Kosowski et al. (2006). The general topic of evaluating luck versus skill among fund managers, and whether they can justify their cost, is heavily studied.

This thesis examines luck versus skill among 107 Norwegian Mutual Funds under the null hypothesis of no true performance. We replicated Kosowski et al.'s (2006) method as it is a highly acknowledged method in distinguishing luck from skill, generating p-values significantly different from a standard t-test. We conclude that the null cannot be rejected for the top performers as they did not generate statistically significant results at a 5% level of significance. The results were the opposite for the bottom performers as they generated significant results in most funds. The results indicate a lack of skill among the top performers; however, the bottom performers were not merely unlucky but also displayed a lack of skill. This is in keeping with the conclusion of Kosowski et al. (2006) and substantiates previous research meaning that the results of studying foreign markets are somewhat transferable to the Norwegian finance markets.

Since our thesis revolves around Norwegian mutual funds, with an 80% of their stocks within the Norwegian market, international trends are less directly impactful. However, global trends and investment strategies impacts Norwegian funds. As we have discussed in our thesis, Jensen (1968) already argued that active mutual funds are not worth the investment. Despite this being the consensus about academics, mutual funds continue to grow worldwide. Only in the data we acquired from VFF, we saw an increase from 38 MNOK to 677 MNOK in assets managed in the Norwegian Mutual Fund Market. This is the same in Norway, we continue to invest in active funds, despite the academic research generally failing to justify these investments. (Fama and French 2010). The findings done is this thesis are greatly impacted by international forces as we implement international performances evaluation tools such as Carhart (1997) four-factor model and bootstrap method of Kosowski et al. (2006)

We focus on Norwegian mutual funds in our thesis, but never mention the biggest fund in Norway, Norges Bank Investment Management (NBIM). They are trying to impact the international trends themselves, moving away from environmentally and unethical investments. This fund is not in Norwegian stocks, but it is an example of how Norwegian investment can impact international trends. Being a flagship for funds all over the planet trying to lead by example. I will talk more about the responsibility the fund has to the Norwegian people later in the reflection note.

When discussing innovation in our scientific approach, we apply the same methods as Kosowski et al.(2006). In this direct manner we are less innovative. We are only innovative the empirical research we contribute to the literature. Using new data and researching if we discover a new conclusion then the researchers before us. To try and produce even better results, having more complete data could impact the results. TITLON has provided us with NAV adjusted, where the managerial fee is already deducted. Specifically, this means if a fund has an alpha equal to zero, the manager can generate a positive alpha, but collects it as fees. It would be fascinating to have the exact managerial fees for the entire period. If we had the exact numbers for this, maybe our conclusions would be different. Maybe we would be able to justify the investment in the Norwegian mutual funds and their managers. In fact, maybe some funds in our sample have a significantly higher fee, thus lowering their alpha making them look like an average fund. While in fact they could have had the most skilled managers. Looking at this from a practical point of view, this could be a challenge, and maybe there is push back on this. However, the results from this could be exiting to examine.

One innovation to improve Norwegian mutual funds would be investing in low-cost index and focusing on new technology trying to optimize these portfolios in order to generate a growth that could be generated without the concern of paying managers their fees for their services. Looking at AI and machine learning and using technology in that way to optimize growth. This is an innovation that could be further examined and could be a new cornerstone in Norway when oil income starts to decline, at some point in the future.

When looking the Norwegian mutual fund market, and we fail to identify skilled managers in our sample, only unskilled managers. Indicating that the managers fail in their responsibility to generate an abnormal return for their investors. Which primarily is their job which can be argued is unethical.

According to Corporate Social Responsibility (CSR) businesses should take responsibility for their impact on people the society around them. These funds accept money from people and say they will use that money to earn more money. According to the findings in this thesis, we cannot claim that this is anything more than a game of chance. At the very least, we need more data or better models to examine it closer.

Taking on a broader spectrum, we can look at the NBIM. They are moving away from environmentally unfriendly investments in favor of more environmentally friendly endeavors. In the words of the famous Milton Friedmann, "The business of business is business". This is probably less true in today's climate because being environmentally friendly, even if it costs, can be an economic advantage. What kind of CSR does NBIM have? Are they more loyal to the Norwegian people, in terms of generating the highest growth? Alternatively, are their focus on sacrificing growth for the better of the planet. One can argue the one does not disqualify the other. However, one can question; is this the best way of using the fortune we, as the Norwegian people, were so lucky to acquire through oil. Maybe a stronger focus on generating a new sustainable income through technology could be a better approach. This way, we can continue to have options in what path we decide to take in the future, while we still have a large oil fund as a safety net.

In concluding this reflection note, we briefly look at the empirical research results in this thesis. We fail to identify any skilled managers in our sample of funds, leading us in the direction of being unable to justify investing in these funds. Despite that, Norwegian mutual funds rapidly grow in value, even when failing to be supported by academic research done worldwide. We investigate the possibility of improving the data, which could lead to different conclusion of this thesis specifically and other papers like it. Finally, in the end, we reflect on the CSR that can be associated with operating actively managed fund under the conclusion reached in this thesis. We touch on what the biggest fund in Norway, NBIM which is a flagship with their enormous resources and the choices of their investment in order to be ethical, environmentally friendly, simultaneously generating the highest possible growth.

This is a difficult question worth exploring further, and really considering what the best option for the future of our country is. Writing this thesis has been a very educational process that has been tough at times, especially the part about RStudio. However, I am happy that we chose to write this topic specifically because I found it very interesting and I learned a lot in the process.